Effects of behavioural and psychological attributes on labour market outcomes in an uncertain economic environment

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Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own original work, that I am the authorship owner thereof (unless to the extent explicitly states) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Date: March 2020

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Abstract

The power of human capital variables in predicting an individual's economic success is well documented theoretically and empirically. However, recently, economists have acknowledged that even with a rich set of controls, residual differences remain unexplained by traditional economic variables. A more recent effort incorporates insights from neighbouring social sciences, including personality psychology, in examining an individual's life outcomes. At the center of this research has been the role of unobservable individual heterogeneity, in particular behavioural and psychological attributes. There is, however, a substantial imbalance in the geographical distribution of this research; the evidence is mostly limited to developed countries, which differ systematically from developing countries. This dissertation aims to address this imbalance. It examines the role of behavioural and psychological attributes in explaining an individual's labour market outcomes in an emerging economy characterized by uncertainty.

The dissertation introduces a novel Zimbabwean matched employer-employee data set that captures key variables of workers' behavioural and psychological attributes. It derives measures of workers' Big Five personality traits, risk and time preferences, and examines their role in explaining labour markets outcomes in the Zimbabwean manufacturing sector. Chapter 2 employs a factor analytical strategy to extract five personality factors from a 15-item Big Five Inventory. The factors - Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism, commonly known as the Big Five - represent the broad dimensions of abstracting an individual's personality. The factor model passes fitness tests, and the extracted factors retain acceptable levels of internal reliability. In addition, the factors mirror the universal distribution of the Big Five personality traits by age and gender.

Chapter 3 examines the role of the Big Five personality traits in explaining labour market outcomes in the Zimbabwean manufacturing sector. To do this, the study controls for the Big Five personality traits in models that estimate sectoral selection, earnings, and job mobility. The empirical findings show that personality traits explain the three labour market outcomes over and above the traditional economic variables. Chapter 4 uses experimental data to construct a risk aversion measure and examines its role in explaining job mobility. The study confirms the empirical findings that risk tolerant individuals are more likely to experience job mobility, as compared to their risk averse peers. This result is robust to a set of controls, including industrial sector fixed effects. Chapter 5 computes measures of worker's time preferences (exponential and hyperbolic discount rates) and examine their role in explaining outstanding salaries. The empirical results suggest that individual and job characteristics - rather than time preferences - explain outstanding salaries. Chapter 6 simultaneously controls for personality traits, risk, and time preferences in labour market outcome models. The study finds empirical support for the simultaneous inclusion of behavioural and psychological attributes in labour market models. Overall, the analysis shows that behavioural and psychological attributes constitute important individual characteristics that are central to the analysis of labour markets.

Abstrak

Die belangrikheid van opvoeding en die bou van individuele kapitaal om iemand se ekonomiese sukses te voorspel is goed gedokumenteer teoreties en empiries. Alhoewel, ekonome het onlangs erken dat selfs met ‘n stel kontrole veranderlikes, dat daar steeds verskille in ekonomiese sukses oorbly wat nie verduidelik kan word deur die onafhanklike en kontrole veranderlikes nie. Deesdae, word insig getrek uit sosiale wetenskappe onder andere persoonlikheid sielkunde wanneer ekonomiese lewensuitkomstes bestudeer word. Hierdie navorsing fokus gewoonlik op verskille tussen mense wat nie ooglopend is nie, spesifiek gedrags en sielkundige verskille. Ongelukkig, kom die meerderheid van hierdie navorsing uit ontwikkelde lande, wat verskil van ontwikkelende lande. Hierdie tesis mik om hierdie balans reg te stel. Dit bestudeer die rol van gedrags en sielkundige faktore in die verduidelik van ‘n mens se arbeidsmark uitkomstes in ‘n ontwikkelende land waar onsekerheid hoog is.

Hierdie tesis stel voor ‘n nuwe datastel waarin werkers in Zimbabwe gepaar word met hul werkgewers en wat belangrike veranderlikes van werkers se gedrags en sielkundige aspekte in het. Dit bevat maatstawwe van werkers se groot 5 persoonlikheidstrekke, risiko en tyd voorkeure en bestudeer hierdie faktore se rol in die verduidelik van individuele arbeidsmark uitkomstes in Zimbabwe se vervaardigings sector. Hoofstuk 2 maak gebruik van ‘n faktor analise strategie om 5 persoonlikheids trekke uit ‘n vyftien faktor groot vyf biblioteek te trek. Die vyf faktore is openlikheid, pligsgetrouheid, Ekstroversie, aangenaamheid en neurotisme. Algemeen bekend as die Groot Vyf - verteenwoordig die breë dimensies van die abstrahering van 'n individu se persoonlikheid. Die faktormodel slaag fiksheidstoetse, en die onttrekde faktore behou aanvaarbare vlakke van interne betroubaarheid. Daarbenewens weerspieël die faktore die universele verspreiding van die groot vyf persoonlikheidseienskappe volgens ouderdom en geslag

Hoofstuk 3 ondersoek die rol van die Groot Vyf persoonlikheidseienskappe in die verduideliking van arbeidsmarkuitkomste in die Zimbabwiese vervaardigingsektor. Om dit te doen, kontroleer die studie vir die Groot Vyf persoonlikheidseienskappe in modelle wat sektorale seleksie, verdienste en werksmobiliteit skat. Die empiriese bevindinge toon dat persoonlikheidseienskappe die drie arbeidsmarkuitkomste bo en behalwe die tradisionele ekonomiese veranderlikes verduidelik. Hoofstuk 4 gebruik eksperimentele data om 'n risiko-aversiemaatstaf te konstrueer en ondersoek die rol daarvan in die verduideliking van werkmobiliteit. Die studie bevestig die empiriese bevindinge dat risiko-verdraagsame individue meer geneig is om werkmobiliteit te ervaar, in vergelyking met hul risiko-sku eweknieë. Hierdie resultaat bly constant selfs wanneer gekontrolleer word vir 'n stel beheermaatreëls, insluitend industriële sektor vaste effekte. Hoofstuk 5 bereken maatstawwe van werker se tydvoorkeure (eksponensiële en hiperboliese verdiskonteringskoerse) en ondersoek hul rol in die verduideliking van uitstaande salarisse. Die empiriese resultate dui daarop dat individuele en werkseienskappe - eerder as tydsvoorkeure - uitstaande salarisse verklaar. Hoofstuk 6 kontroleer gelyktydig vir persoonlikheidseienskappe, risiko en tydvoorkeure in arbeidsmarkuitkomsmodelle. Die studie vind empiriese ondersteuning vir die gelyktydige insluiting van gedrags- en psigologiese eienskappe in arbeidsmarkmodelle. Oor die algemeen toon die ontleding dat gedrags- en

psigologiese eienskappe belangrike individuele kenmerke uitmaak wat sentraal staan in die ontleding van arbeidsmarkte.

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List of acronyms and abbreviations

BFI	Big Five Inventory
CFA	Comfirmatory factor anaylsis
CFI	Comparative fit index
EFA	Exploratory factor analysis
FA	Factor analysis
FDI	Foreign direct investment
KMO	Kaiser-Meyer-Olkin
LGC	Latebt Growth Curves
MEPLMAZ	Matched Employer-Employee Panel Data for Labour Market Analysis in Zimbabwe
MDG	Millennium Development Goals
MI	Modification Indices
MoF	Ministry of Finance
MSA	Measure of sampling adequacy
NEO-PI-R	Revised NEO Personality Inventory
OCEAN	Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism
OLS	Ordinary least squares
PCA	Principal component analysis
RMSEA	Root Mean Square Error of Approximation
SALDRU	Southern African Labour Development Research Unit
SRMR	Standardised Root Mean Square Residual
TDA	Trait Descriptive Adjectives

CHAPTER 1

INTRODUCTION AND RESEARCH AIMS

1.1 INTRODUCTION

Considerable progress has been made in explaining individuals' labour market trajectories and income inequality in the empirical literature. However, residual differences remain unexplained, even within a range of standard economic variables (including human capital). What explains the difference has been a topic of recent interest. Empirical studies have partially amended the bias towards easily measurable demographic and job characteristics. Behavioural and psychological attributes constitute significant, and yet often neglected, sets of determinants of various life outcomes (Almlund *et al*., 2011; Borghans *et al*., 2008; Brunello & Schlotter, 2011). Within a set of behavioural and psychological attributes, personality traits, risk, and time preferences have been added to the empirical toolkit in studying economic outcomes, including those related to labour markets (Bonin *et al*., 2007; Borghans *et al*., 2011; Cunha *et al*., 2006; Falco, 2014; Gensowski, 2018; Heckman *et al*., 2011; van Huizen & Plantenga, 2014).

Labour market earnings constitute a major source of income for most individuals in developing countries. Economists have thus taken a natural interest in building theoretical models that examine the sources of differences in individuals' levels of economic success. Search and match theories have been at the heart of analysing labour markets (Burdett, 1978; Jovanovic, 1979; Mortensen, 2011; Mortensen & Pissarides, 1994). They however, fail to exhaustively explain observed differences in labour market outcomes, even with a rich set of controls. In Zimbabwe, where decades of economic challenges resulted in higher proportions of workers being in precarious jobs and rising long term unemployment, understanding which attributes contribute to labour market success is imperative to understanding the widening income inequality.

The study introduces a novel dataset, the Matched Employer-Employee Panel Data for Labour Market Analysis in Zimbabwe (MEPLMAZ), a two-wave survey micro dataset of the Zimbabwean manufacturing sector. Through this rich data set, the contribution of this dissertation is broadly twofold. First, we advance existing knowledge on the derivation of measures of personality traits, risk and time preferences, profiling them amongst a sample of Zimbabwean manufacturing workers. At the heart of this is identifying sources of heterogeneity in human behaviour. Secondly, we challenge our current understanding of factors that explain variations in individuals' employment outcomes. Our analysis follows research documenting that personality traits (Gensowski, 2018; Heckman, 2011b; Nyhus & Pons, 2012), risk aversion (Dohmen, 2014a; Falco, 2014), and time preferences (van Huizen & Alessie, 2015; Perez-Arce, 2017) are relevant in understanding individuals' employment outcomes related to occupations, earnings and job mobility.

Using this unique Zimbabwean data set, we hope to advance our understanding of the static and dynamic aspects of an emerging economy's labour markets. We focus on the following specific questions, which we pose here and address in the following chapters:

i) What are the personality traits of Zimbabwean manufacturing sector workers and how are they distributed?

ii) What is the role of personality traits in explaining employment outcomes in the Zimbabwean manufacturing sector?

iii) Does risk aversion explain observed job mobility patterns amongst manufacturing sector workers?

iv) Can experimentally elicited measures of time preferences explain outstanding wages in Zimbabwean manufacturing?

v) What is the combined effect of behavioural and psychological attributes on labour market outcomes?

By examining these questions, we address an empirical lacuna that currently exists within developing country contexts.

1.2 BACKGROUND AND CONTEXT OF STUDY

The economic crisis that hit Zimbabwe (2000-2009) has brought a legacy of rising long-term unemployment, underemployment, and worsening income inequality. The period, referred to as the "lost decade", witnessed massive deindustrialisation of a previously diversified and vibrant manufacturing sector (Kanyenze *et al*., 2011). Capacity utilisation fell from an average of 83% (1980-1989) to record levels of 8% in 2008. Despite rebounding to 57% in 2011 after the adoption of a multi-currency system, the improvements did not last long; it fell to 36.3% in 2015 (CZI, 2015). Ever since, it has never gone beyond 50%. The effects on employment have been evident. Formal manufacturing employment declined from 206 000 in 1991 to 127 300 in 2009. This trend continued, with at least 4 610 firms closing between 2011 and 2014, resulting in at least 55 443 job losses (MoF, 2015). The contraction of formal employment resulted in an expanding informal sector.

The Labour Force and Child Labour Survey (2014) reports that unemployment, measured using the broad definition [1], rose from 10.7% in 2011 to 11.3% in 2014. A majority of the employed population (94.5%) in 2014 were in informal jobs, up from 84% reported in 2011 (ZIMSTAT, 2015). The manufacturing sector - which is predominantly male (84.7%) - contributes 4% to employment. Agricultural jobs (67.2%) still dominate employment in Zimbabwe. Unsurprisingly, most workers (66% males and 83% females) are classified under vulnerable employment, according to the Millennium Development Goals (MDGs). The nature of jobs and employment contracts makes a

[1] A distinction between the broad and strict definition of unemployment is the relaxation of the "seeking work" criterion. In economies like Zimbabwe, conventional means of seeking for work are of limited relevance; the labour market is largely unorganized and labour absorption is inadequate. In actual fact, the labour force is largely self-employed.

particularly interesting case. A majority (59%) are own-account workers (farming), 16% are paid employees on permanent contracts, 14% are own-account workers (other), and the rest are in paid casual or temporary work.

The manufacturing sector has struggled to add jobs amid a myriad of challenges, including macro-economic policies that continue to antagonise its revival. Policy inconsistencies and the lack of policy clarity at the macro level has created a cloud of uncertainty in the economy. The rushed fast track land reform programme and the indigenisation policy, for instance, fuelled concerns about the respect for property rights. These have been cited as scaring potential foreign direct investments (FDI) and the economy remains depressed. Firms have adopted a number of survival strategies, including downsizing, diversification, and altering employment contracts. According to the Labour Force and Child Labour Survey (2014) retrenchments rose sharply from below 5 000 in 2005 to over 87 000 by end of 2013. Cumulatively, retrenchments account for 227 369 job loses between June 2011 and May 2014; 99% of them were economically active (ZIMSTAT, 2015). At the aggregate, the manufacturing sector (17.8%) was only second to the agricultural, forestry and fishing sector (19.8%) in contributing to retrenchments. Unlike developed countries with tight labour markets, the Zimbabwean labour market can be best described as slack. Most of the retrenched (80.1%) were reemployed but mostly in precarious jobs; only 18.4% secured formal jobs, 25.2% informal sector jobs and the majority (56.1%) were involved in household jobs.

The MEPLMAZ, a recent survey, shows that 40% of workers in manufacturing report outstanding wages in 2016. Interestingly, they have stayed in their jobs. We can infer a number of plausible reasons to explain this phenomenon from the survey. Firms cannot afford the retrenchment cost; the labour laws stipulates that the retrenched should be paid severance packages proportionate to their tenure. Workers are discouraged from voluntarily leaving jobs since they would lose this claim. Secondly, workers may be waiting for the firm to do better, with the hope that they will be paid when this happens. Thirdly, it may be that workers who are prepared to accept not being paid fully have different personality traits, risk and time-preference profiles. Another reason could be limited outside options. Against this background, we conduct five related investigations that empirically examine the role of behavioural and psychological attributes on observed differences in labour market outcomes.

1.3 MOTIVATION AND RESEARCH AIMS

Standard economic models focus on human capital variables in examining variations in labour market success (Almulund *et a*l., 2011; Borghans *et al*., 2008). However, despite substantial evidence in support of human capital variables, there are residual differences that remain unaccounted for (Cunha & Heckman, 2006; Heckman, 2011). Recently, economists have incorporated insights from neighbouring social sciences to account for the role of unobservable heterogeneity in human behaviour in modelling life outcomes. Personality traits and individuals' economic preferences - in particular - are amongst a set of core variables that capture heterogeneity

in human behaviour. However, much of the existing research effort is concentrated on developed nations, where nationally representative data sets are available. In this dissertation, we extend a new data set from a developing country to address this empirical challenge.

The empirical gap is surprising, given the massive structural differences between developed and emerging countries. Identifying the abilities and attributes that contribute to success in environments of constrained economic opportunities is central to understanding sources of economic inequality. Behavioural and psychological attributes are a vital cog in the economic decision making matrix, as individuals weigh alternatives to maximise incomes. Zimbabwe makes a particularly interesting case; the economic environment is characterised by uncertainty, and formal labour markets are inefficient and slack. On the other hand, the informal sector has grown to be a significant source of employment. A clear understanding of how workers sort between sectors and decide on moving between jobs is thus central to any understanding of labour markets and income distribution. We add to the growing literature on the importance of behavioural and psychological attributes on urban labour markets in emerging economies. Our data is suited for a rich analysis of the effects of three main behavioural measures: personality traits, and risk and time preferences on individuals' static and dynamic employment outcomes.

1.3.1 Personality traits in Zimbabwean manufacturing

Recently, the role of personality in explaining economic outcomes ranging from education, health and labour has received special attention. The Big Five model of personality traits that defines personality across five broad dimensions - Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN) - has been added to economists' empirical toolkit. However, absence of data sets that capture personality data has restricted existing evidence to developed countries. Standard Big Five instruments - including the Revised NEO Personality Inventory (NEO-PI-R, 244 items) - can take a long time to administer and are difficult to include in multi-module surveys. Short, efficient instruments, that suit time constraints ordinarily faced by researchers, have thus been developed and validated though mostly for developed countries (Anger *et al*., 2017; Gosling *et a*l., 2003; Lang *et al*., 2011). Expanding the universe of evidence to developing countries - using a reduced item instrument - can contribute to our understanding of the applicability of this model in the study of economic outcomes.

In Chapter 2, we revisit existing studies that determine personality traits and provide evidence for an adult sample of manufacturing workers, using a reduced item instrument. Using factor analysis, we extract five factors that explain our personality data. The confirmatory factor model passes fitness and the factors satisfy requirements for internal reliability. We further examine their distribution by a set of demographic characteristics; we find that personality traits differ by age, gender, ethnic group, and location. The study is an important first step towards understanding unobservable individual

heterogeneity and forms the basis for subsequent empirical examination of individuals' employment outcomes.

1.3.2 Personality traits and labour market outcomes in Zimbabwe

Recent, albeit limited evidence in economics, points to the significance of so-called non-cognitive skills in the empirical analysis of life outcomes ranging from earnings and education to health (Almlund *et al*., 2011; Brunello & Schlotter, 2011). The Big Five personality model, in particular, explains choice of occupation (Derya & Pohlmeier, 2011; Villa & Sahn, 2015), earnings (Gensowski, 2018; Heineck, 2011; Mueller & Plug, 2006; Nyhus & Pons, 2012) and job mobility (Bartolec, 2018; Zimmerman, 2008). The key findings in this literature is that - in addition to traditional economic variables - personality traits explain labour market outcomes. Much of this evidence comes from developed countries[2], yet it is conceivable that personality traits may be particularly relevant in developing countries' labour markets.

We extend this literature to an emerging economy characterised by economic uncertainty and examine the role of personality traits in explaining variations in individuals' labour market outcomes. Specifically, we estimate standard economic models of sectoral occupation, earnings, and job mobility and control for the Big Five personality traits. Furthermore, we account for endogenous selection in the fashion of Durbin and McFadden (McFadden, 1973) in the earnings equation. Our findings show that personality explains individuals' occupational sector; Conscientiousness and Extraversion explain a higher likelihood of formal employment relative to both forms of informal sector employment. The other three traits, however, have an opposite effect. Earnings estimates suggest that, in addition to a direct relationship, personality traits have an indirect effect on individuals' earnings through occupational selection. We find evidence confirming that personality traits explain job mobility; in addition, they moderate workers' mobility choices given past employment shocks.

1.3.3 Risk aversion and job mobility in Zimbabwe

The theory of decision making under uncertainty entails that individuals' attitude towards risk is crucial in a variety of circumstances that are central to understanding human behaviour. The theory suggests that risk aversion influences how economic agents make decisions that involve outcomes that are not entirely certain. One inescapable decision relating to workers is whether to move from one job to another. Traditionally, job changes have been studied in the context of on-the-job search and match theories (Burdett, 1978; Johnson, 1978; Jovanovic, 1979). Much focus has been on wages, and non-wage (human capital, job, and firm) characteristics (Baird, 2017; Bonhomme *et al*., 2016; Hwang *et al*., 1998). The existence of search and information frictions that prevent workers

[2] An exception is a study done in Madagascar, which includes personality traits in the study of occupational selection and earnings (Villa & Sahn, 2015).

from immediately matching with optimal jobs implies that changing jobs is inherently risky (Argaw *et al*., 2017; van Huizen & Alessie, 2016).

Emerging evidence points to the significance of risk aversion in explaining labour market outcomes, ranging from self-employment, earnings, occupations, and job mobility (Ahn, 2010; Argaw *et al*., 2017; Bonin *et al*., 2007; Caliendo *et al*., 2009; Falco, 2014; Fouarge *et al*., 2014; van Huizen & Alessie, 2016; Jaeger *et al*., 2010). In Chapter 4, we derive risk aversion measures from a lab-in-the field experimental task - with real monetary payoffs - and investigate their role in explaining observed job mobility patterns. We find that risk averse individuals are less likely to change jobs compared to their risk tolerant peers, this relationship is significant to the inclusion of a number of controls including industrial subsector fixed effects. Our results confirm earlier findings, and reinforce the need to account for heterogeneity in risk preferences when estimating individuals' economic outcomes.

1.3.4 Outstanding salaries: Do time preferences matter?

Every day, individuals encounter situations where they have to make decisions involving benefits and costs that occur at different periods. Such choices include whether or not to accept a salary delay. Intertemporal decision-making has been a characteristic of many economic models and a salient feature of human capital theory (Golsteyn *et al*., 2014). Individuals with high discount rates invest less in the future, compared to their peers with lower discount rates. Substantial evidence shows that time preferences explain a number of economic outcomes (Borghans & Golsteyn, 2006; Cadena & Keys, 2015; DellaVigna & Paserman, 2005; Drago, 2006; Golsteyn *et al*., 2014; Perez-Arce, 2017). Despite generating interest in labour economics - including the earnings literature - whether they explain outstanding wages remains an open question.

Most workers in emerging economies, including Zimbabwe, rely on labour market earnings to finance their daily needs; a delay in salary payment inevitably has far-reaching implications on welfare, especially for single earner households. It is conceivable that time preferences potentially explain outstanding salaries amongst manufacturing workers. In this study, we investigate if time preferences explain outstanding wages. To do this, we compute workers' discount rates - both exponential and hyperbolic - using data gathered from a laboratory experiment with real monetary payoffs. Our estimates of outstanding wages show a positive association between patience and outstanding salaries, the relationship is however insignificant. In addition, we find that firm and job characteristics explain outstanding wages.

1.3.5 Personality traits, risk and time preferences: Labour market analysis in Zimbabwe

In Chapter 6, we consider the joint effects of behavioural and psychological attributes on employment outcomes, focusing on sectoral occupation, earnings, and job mobility. Our analysis follows from the findings in Chapter 3 to 5, showing the significance of personality traits, risk and time preferences in the analysis of labour markets. We are motivated by filling the existing empirical gap, as most studies

look at these attributes in isolation when estimating life outcomes (yet they constitute distinct measures of human behaviour). The absence of data sets that simultaneously capture both sets of behavioural and psychological attributes could possibly explain this. Our data set offers us that flexibility; hence, we take an interest in providing a unified analysis of their effects on employment outcomes within the Zimbabwean context.

1.4 THE DATA

The data that makes this study possible comes from the MEPLMAZ data set, a recent survey of the Zimbabwean manufacturing sector. The Southern African Labour Development Research Unit (SALDRU) at the University of Cape Town undertook the survey across two waves (2015 -2016). The survey sought to gain insights into how economic developments in Zimbabwe - post the economic crisis - affected the manufacturing sector and labour markets. The survey sought to understand how firms manoeuvred the economic downturn, as well as how workers transitioned within and between jobs. The survey captured firm and worker information using a set of questionnaires across Zimbabwe's main industrial cities. It focused on seven industrial subsectors across both formal and informal sector, covering different sizes (firms ranging from micro to large firms). The worker survey was multi-topic, and was the first to capture participant's behavioural and psychological attributes, in addition to the socio-economic and demographic information that typically characterises labour market surveys.

The initial wave (2015) interviewed 194 formal firms and 1 385 formal employees, and 132 informal firms (self-employed) and 175 informal employees. Using participants' unique identification codes, the survey tracked the employment states of subjects a year later (in 2016). This gave us a unique two-wave survey data that we used for the purpose of this study. Further details on the sample selection (stratification) strategy and survey instruments will be discussed in subsequent chapters.

The strength and novelty of our study lies in the use of a very rich data source. The data set captures measures of individuals behavioural and psychological attributes; personality traits, risk, and time preferences. Subjects completed a reduced item instrument of the Big Five personality traits inventory that rates how they perceive themselves on 15 personality traits statements. A particular benefit of a reduced item instrument is its compatibility with multi-module surveys (when the researcher time is constrained). In addition, it has been shown to explain economic outcomes, including those related to labour markets (Anger *et al*., 2017; Heineck, 2011; Heineck & Anger, 2010; Nyhus & Pons, 2012). Furthermore, subjects took part in incentivised lab-in-the-field experiments (with real monetary payoffs) designed to elicit workers' risk and time preferences. Incentivised experiments are considered the gold standard in economics for capturing individuals' economic preferences. The two-wave survey, which is the first of its kind for Zimbabwe, enables us to investigate both the static and dynamic aspects of individuals' labour market outcomes. No other

data sets have permitted researchers to investigate the effects of behavioural and psychological attributes on employment outcomes, in an economic environment characterised by uncertainty.

1.5 SUMMARY AND THESIS OUTLINE

Overall, the thesis finds evidence supporting the inclusion of behavioural and psychological attributes in models of labour market outcomes. How do we define and measure personality traits? Chapter 2 addresses this question by revisiting the Big Five personality traits literature and proposing a factor analytic procedure that extract factors that define our personality data. We show that reduced item instruments can capture individuals' Big Five personality traits. In Chapter 3, we examine the relevance of the extracted personality traits on individuals' employment outcomes related to sectoral occupation, earnings, and job mobility. Chapter 4 develops experimentally elicited risk aversion measures, and examines how they relate to workers' job mobility. We find that risk averse workers are less likely to change jobs compared to their risk tolerant peers. Chapter 5 computes measures of time preferences using data from an incentivised experiment and examines the relationship between time preferences and outstanding salaries. As an extension to Chapters 2 to 5 - which are mainly concerned with examining the role of personality traits, risk, and time preferences on employment outcomes in isolation - Chapter 6 provides their joint estimates on employment outcomes. Chapter 7 concludes this study, and provides recommendations for future research.

CHAPTER 2

PERSONALITY TRAITS IN THE ZIMBABWEAN MANUFACTURING SECTOR

ABSTRACT

In recent years, the inclusion of personality trait measures in national surveys has become more common as researchers sought to investigate the effects of behaviours and attitudes on variations in individual economic outcomes. The Big Five model, in particular, has proven to be an empirical workhorse in this regard. Studies have increasingly used reduced item instruments, which are easy to accommodate in multi-module questionnaires. In this study, we extend this research to an adult working population in the Zimbabwean manufacturing sector, using a reduced item instrument to determine personality traits. In particular, we employ factor analysis to extract five factors that explain our personality data. Given the breadth of the questionnaire items, they could not capture all the facets that define the Big Five, but rather capture a few facets that are highly correlated with the Big Five. The factors return acceptable levels of internal reliability. We checked for differences in the distribution of personality traits by a set of demographic characteristics and found that personality traits differ by age, gender, ethnic group, and location. The study provides an important first step towards understanding unobservable individual heterogeneity. Future research can profit from relating the computed measures to socio-economic indicators. In particular, we use the computed measures to investigate the effects of personality traits on employment outcomes.

Keywords: Personality Traits, Big Five Model

2.1 INTRODUCTION

The role of personality in explaining economic outcomes related to labour markets has received special attention in recent years. The Big Five model, that measures personality traits across five dimensions - Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN), in particular - has begun to be used to investigate the importance of personality to labour market outcomes (Costa & McCrae, 1999). In this literature, there is a growing consensus that personality traits matter in explaining and predicting individual differences in labour market outcomes (Almulund *et al.*, 2011; Borghans *et al.*, 2008a; Brunello & Schlotter, 2011; Dohmen, 2014b). The Big Five model was also at the centre of the Facebook/Cambridge Analyitica scandal linked to the Trump campaign in the recent US elections. The revelations have shown how knowledge of individual personality profiles, using advanced machine learning, can help understand (and influence) individual behaviour and - in this instance - electoral choices[3].

[3] https://www.theguardian.com/news/2018/may/06/cambridge-analytica-how-turn-clicks-into-votes-christopher-wylie

While generating and instigating new research questions in applied economics, the challenge has been to come up with reliable and robust measures of the Big Five personality traits (Gosling *et al*., 2003; Lang *et al*., 2011; Rammstedt & John, 2007). There are at least two aspects of this research, which require further investigations to understand the general applicability of the Big Five model to labour markets. The first is coverage: existing studies are confined to convenience samples, often college students. Moreover, there are few national surveys in developing countries that incorporate personality modules, thus much of the research has been restricted to high-income countries. The second is that the instrument used often varies between studies. Expanding the universe of studies to different contexts and using different instruments can contribute to our understanding of the applicability of this model.

There is a paucity of research on the Big Five model in low-income countries in general, and Zimbabwe specifically. Published research including the Zimbabwean population is limited and - with the exception of Piedmont *et al*. (2002) - there is no other study exclusively done on Zimbabwe. Other studies on the Big Five involving Zimbabwean participants were mainly multi-cultural[4]. Piedmont *et al*. (2002) drew participants from a predominantly student population and used the NEO-PI-R 244 item instrument. Bleidorn *et al*. (2013) used the 44-item Big Five inventory (BFI-44) to sample 758 participants (65% females) between the ages of 16 and 40. Schmitt *et al*. (2007) used both the BFI-44 and the NEO-PI-R instrument for Zimbabwean participants. Standard Big Five instruments - including the NEO-PI-R questionnaire - can take a long time to administer and can be difficult to combine with other modules. In this regard, short efficient instruments (the 10-item and 15-item BFI) that suit these constraints have been developed and validated but mostly in developed countries (Anger *et al*., 2017; Gosling *et al*., 2003; Lang *et al*., 2011). In this research, we use a reduced form of a 'standard' Big Five questionnaire: a 15-item instrument to extend research on these character traits into a broader sample of Zimbabwean adult workers.

The main objective of this study is to revisit existing empirical studies on personality traits determination by using a different methodology on a novel data set from a low-income country. More precisely, the methodology that we adopt uses factor analytic techniques to extract latent factors that measure individuals' personality. Reduced item studies typically average scores from item tests to determine one's personality traits. This practice however, rests on the assumption that the items carry the same weight in the factor model, which is not always the case. Averaging trait scores may suffer from including items that do not necessarily correlate with the trait. In this study, we correct for this using factor analysis. This statistical technique reduces the dimensionality of the data without arbitrarily imposing that each of the three captured indicators are related and have equal weights in explaining a given trait factor (Cattan, 2013).

[4] Studies including Zimbabwean participants are mainly cross-cultural; some sought to validate the universality of the Big Five model (Schmitt *et al.*, 2007; McCrae *et al.,* 2008) and the other, the patterns of personality development (Bleidorn *et al*., 2013). In both studies, the Big Five model was replicated and reliability coefficients for Zimbabwean participants were acceptable.

Common findings from studies profiling individual personality traits confirm age and gender differences in personality traits. Women have been consistently reported to be more Agreeable and Neurotic than males (De Bolle *et al*., 2015; Weisberg *et al*., 2011), and these differences have been shown to explain gender differences in economic outcomes for example earnings (Cattan, 2013; Nikolaou, 2012; Nyhus & Pons, 2012). In respect of age, consistent evidence shows that Agreeableness and Conscientiousness increase, while Neuroticism declines as individuals traverse adulthood (Briley & Tucker-Drob, 2014; Specht *et al.*, 2011). Both biological and environment factors explain the process of age-related changes in personality traits (Boyce *et al.*, 2013, 2015; Derya & Pohlmeier, 2011). Interestingly, labour market experiences constitute part of environmental factors linked to changes in personality traits. For instance, studies report an increase in the personality trait Openness to Experience after losing jobs (Anger *et al*., 2017; Bleidorn *et al*., 2018).

The study provides a first account on the determination of Big Five personality traits using a reduced item instrument for a heterogeneous sample of Zimbabwean manufacturing workers. Understanding personality traits helps unpack an individual's strategy function when confronted with uncertainty. For instance, it is argued in literature that - in situations of fundamental uncertainty - people rely on a series of conventional behaviours to make decisions and base their actions (Borghans *et al*., 2008; Heckman, 2011; Heineck & Anger, 2010). By determining individual personality traits, we can further investigate through econometric means how these unobservable, non-cognitive skills explain individual differences in economic outcomes, through the labour market. From a policy point of view, understanding the age profile distribution of traits helps in suggesting policy interventions that foster trait reorientation to affect individuals' future life outcomes. Indeed, given the growing importance placed on soft skills (including personality traits) in the labour market (Deming, 2017; Dodge *et al*. 2014); early childhood interventions can help improve individuals economic outcomes.

The following section discusses relevant research on the Big Five model of personality traits. We review literature on personality trait determination, their distribution by gender, across age groups, and by geographical location. In Section 2.3, we describe our data followed by the methods for measuring personality traits in section 2.4. We present and discuss estimation results of the factor model and investigate for trait differences by demographic variables in section 2.5. Section 2.6 gives a summary and conclusion for the study.

2.2 EXISTING EMPIRICAL WORK

2.2.1 The Big Five Model

There is no agreed definition of personality; however, the distinct component of personality are personality traits (Dohmen, 2014). Personality traits are:

> *"…the relatively enduring patterns of thoughts, feelings, and behaviours that reflect the tendency to respond in certain ways under certain circumstances*." (Roberts, 2009, p.140).

That is, an individual who has a high score in a given personality trait is more likely to exhibit behaviours reflective of that trait more often, and to a greater extent, as compared to someone who scores low in that trait (Weisberg *et al*., 2011). A number of metrics have been put forward to measure personality traits; these include, self-esteem (Rosenberg, 1965), Locus of Control (Rotter, 1966), Eysenck's (1967) Extraversion, Stability and Psychoticism model and the Big Five model (Costa & McCrae, 1999). Of these models, the Big Five model has gained prominence in personality psychology and there is consensus that it defines prominent individual differences in personality (see John & Srivastava, 1999; Soto & John, 2009). The model identifies personality traits along five main domains:

i) Extraversion defines one's orientation towards being assertive, ambitious, dominant, energetic, and looking for leadership roles. Extraverted individuals find it easy to develop networks, and this arises from their sociable nature;

ii) Neuroticism describes individuals' tendency to be emotional, pessimistic, easily offended, and vulnerable to stress related disorders; it essentially is a negative specification (Hilger *et al*., 2015);

iii) Openness to Experience defines an individual's ability to seek new challenges and explore novel ideas. Individuals who score high in this trait are innovative, creative, and have an eagerness to explore new ideas. Apart from the intellectual curiosity aspect of this trait, these individuals desire autonomy and sometimes non-conformity;

iv) Conscientiousness defines an individual's tendency to work hard, to be efficient and dutiful. These individuals strive for achievement, are organised, and motivated. They have an inclination towards rule-following and exhibit planned - instead of spontaneous - behaviour (Caliendo *et al*., 2014); and

v) Agreeableness defines individuals' orientation towards being forgiving, cooperative, trusting and altruistic. Low values exhibit a tendency to be self-centred (Caliendo *et al*., 2014).

The development of personality traits models, including the Big Five model, dates back to Allport & Odbert's (1936) lexical hypothesis, which argued that prominent individual differences are encoded in language (John & Srivastava, 1999). They identified almost 18 000 personality-describing words from the unabridged English dictionary. Cattell (1943) extended this work to provide a systematic framework that distinguishes and orders individuals' differences in behaviour and experiences. Using both semantic and empirical clustering procedures, Cattell (1943) reduced Allport and Odbert's initial list to approximately 4 500 (Goldberg *et al*., 1990). He further conducted oblique factor analyses on the reduced set of variables and identified 16 Personality Factors (16PF).

Cattell's (1943) findings stimulated research on the dimensional structure of trait ratings. Starting with Fiske (1949) and subsequently studies[5] in the 1960's, a five factor structure was derived. Lewis Goldberg further developed this work and labelled the factors the "Big Five" (John & Srivastava, 1999; McCrae & John, 1992). Since then, the model has been replicated in different environments and there is consensus that personality traits can be summed in five broad, higher order factors (McCrae & John, 1992; John & Srivastava, 1999).

This marked a major success in the field of personality psychology, as a consensual structure for defining personality traits was identified (John & Srivastava, 1999a). To date, most personality psychologists agree that the Big Five personality constructs provide a comprehensive, acceptable and sufficient frame that defines the structure of core personality traits. Not surprisingly, the wealth of knowledge that came from these findings has instigated much research in the neighbouring disciplines of psychology, including economics (Borghans *et al.*, 2008; Almulund *et al*., 2011; Heckman, 2011).

2.2.2 Measuring the Big Five

Personality traits, like many psychological constructs, are not directly observable. Multi-item instruments of varying lengths have been developed, tested, and validated to measure the Big Five personality traits. The NEO-PI-R by Costa & McCrae (1985) is the most comprehensive of them all. It comprises 240 items, which capture six specific facets, defining each dimension of the Big Five. Each broad Big Five domain incorporates a number of more-specific traits that are related, but also distinguishable. Such traits, referred to as "facets" of the Big Five, comprise a set of adjectives designed to capture individuals' thoughts, feelings and behaviours (see Appendix A, Table A.1). An example, for instance, is the Agreeable factor, that is comprised of six facets (trust, straight forwardness, altruism, compliance, modesty, and tender-mindedness), each defined by a set of adjectives. The major limitation of this instrument however, is that it is too long and this may impose a cognitive burden on respondents since it requires relatively higher levels of concentration (Ryser, 2015; Topolewska *et al*., 2014; Viinikainen & Kokko, 2012). Amongst a growing list of validated Big Five personality instruments are the 100 Trait Descriptive Adjectives (TDA) by Goldberg (1992), the 60-item NEO Five-Factor Inventory (NEO-FFI) by Costa & McCrae (1992) as well as the 44-item BFI by John & Srivastava (1999).

Although shorter, the 44-item BFI may still be too long for multi-topic surveys, especially when there is a time constraint (Heineck & Anger, 2010; Rammstedt & John, 2007). The growth of interdisciplinary research involving the field of personality psychology, in particular, spurred demand for inclusion of individuals' personality modules, especially in nationally representative surveys (Heineck & Anger, 2010; Topolewska *et* al., 2014). Shorter versions of the Big Five instruments - including the 15-item (Anger *et al*., 2017; Heineck & Anger, 2010; Lang *et al*., 2011) and the 10 item

[5]Tupes & Christal (1961), Norman (1963) & Borgatta (1964) are some of the studies that confirmed a five-factor structure.

(Gosling *et al*., 2003; Rammstedt & John, 2007) - have been developed and shown to capture these traits. An example of a 15-item instrument from Lang *et al.* (2011) is given below:

On a scale of 1 to 5, rate how the following statements describe you (1 = Disagree strongly and 5 = Agree strongly).

I see myself as someone who:

i) Worries a lot (N)
ii) Gets nervous easily (N)
iii) Remains calm in tense situations (N, recoded)
iv) Is talkative (E)
v) Is outgoing, sociable (E)
vi) Is reserved (E, recoded)
vii) Is original, comes up with new ideas (O)
viii) Values artistic, aesthetic experiences (O)
ix) Has an active imagination (O)
x) Is sometimes rude to others (A, recoded)
xi) Has a forgiving nature (A)
xii) Is considerate and kind to almost everyone (A)
xiii) Does a thorough job (C)
xiv) Tends to be lazy (C, recoded)
xv) Does things efficiently (C)

To date, there are a number of panel studies at a national scale that include individuals' personality information using reduced item instruments[6], though mainly in developed countries. There is evidence that they do capture the prototypical core of each of the Big Five personality traits. In particular, reduced item instruments produce high correlations with full-scale measures (Gosling *et al.*, 2003; Lang *et al*., 2011; Rammstedt & John, 2007). Despite this, comparing these short instruments with the longer 240-item NEO-PI-R, for instance, shows that they do not adequately capture all the facets of the five factors, which may imply that some facets are not represented (Gosling et al., 2003; Ryser, 2015). We fill the empirical gap in respect of developing countries by testing for the psychometric properties of a reduced item instruments using Zimbabwean data.

Big Five instruments rate how well a set of questions or adjectives describe an individuals' personality, typically on 5-point and 7-point Likert scales. Upon capturing item scores, the immediate challenge is to fit the data into a structure that accurately identifies the Big Five traits. Big Five personality studies have mainly employed three methods: factor analysis (FA), principal component analysis (PCA) and averaging item scores. We summarise the literature on determination of

[6] Large-scale panels are increasingly including psychological self-report instruments, for instance the German Socio- Economic Panel (SOEP), the British Household Panel Study (BHPS) and the Household, Income, and Labour Dynamics in Australia survey (HILDA).

personality traits in Table 2.1, focusing on the instrument used in the study and the main methodological framework employed to determine the personality measures.

Table 2.1: Studies determining the Big Five personality traits

Author	Country	Instrument	Methodology
Anger *et al*. (2017)	German	15 item	Mean score
Hee (2014)	Malaysia	44 item BFI	Factor analysis
Ryser, 2015	Switzerland	10 item & 15 item BFI	Factor analysis
Heineck & Anger (2010)	German	15 items BFI	Mean scores
Rammstedt & John (2007)	German	10 items, 44 BFI	Mean scores
John & Srivastava (1999)		44-BFI, NEO- FFI, TDA	Factor analysis
Cobb-Clark & Schurer (2012)	Australia	36 items	Factor analysis
Gosling *et al*. (2003)	German	10 Item measures	Mean scores
Schmitt *et al*. (2007)	Zimbabwe	NEO-PI-R (240)	Factor analysis
McCrae *et al*. (2005)	Multi-country	NEO-PI-R (240)	PCA
Viinikainen & Kokko (2012)		60 item NEO-FFI	Mean scores
Villa & Sahn (2015)	Madagascar	60 item NEO-FFI	Factor analysis
Cattan (2013)	America	30 item	Factor analysis
Wortman *et al*. (2012)	Australia	36 item	Factor analysis
Lang *et al*. (2011)	German	15 item BFI	Factor analysis
Nyhus and Pons (2012)	Netherlands	15 item BFI	Mean scores
Allemand *et al*. (2015)		60 item NEO-FFI	Factor analysis
Allemand *et al*. (2007)		60 item NEO-FFI	Factor analysis
Bleidorn *et al*. (2009)	Multi-country	NEO-PI-R 240 items	
Topolewska *et al*. (2014)		20 item IPIP	Factor analysis
Gurven *et al*. (2013)	Bolivia	44 item BFI	PCA

Source: Author, 2019.

Some studies average test scores as a way of coming up with trait measures (Gosling *et al*., 2003; Rammstedt & John, 2007; Viinikainen & Kokko, 2012). Despite its computational simplicity, this approach arbitrarily imposes that each of the indicators are related and have equal weights in explaining a given trait factor. This, however, may not the case (Borghans *et al*., 2011; Cattan, 2013).

In cases where the instrument is being used for the first time and there is no existing personality data for the sample, there is a need to establish whether the indicators measure the concept the researcher intents to measure within the research context (Hee, 2014). For instance, in validating the 10-item questionnaire, Rammstedt & John (2007) administered the BFI-44 instrument and the reduced version item questionnaire. In addition, within their sample, there were individuals whose personality data had been captured before using a NEO-PI-R instrument. The study checked for and found evidence of convergent validity (high correlations) between these instruments. High correlations were reported for the mean scores from the 10-item instrument and the factors extracted from the BFI, as well as the NEO-PI-R. In our case, there is no existing personality data for our sample and we cannot check for instrument convergent validity. We rely on FA methods, following other studies (for example Hee, 2004; Gurven *et al*., 2013; Topolewska *et al*., 2014) to examine if the indicators measure the same concept as the Big Five factors.

Factor analysis (FA) is a set of statistical techniques employed with the dual objective of reducing the dimension of multivariate data and providing a more parsimonious appreciation of the data (Hayton *et al*., 2004). A factor is an unobservable variable that influences a number of observed measures (indicators) and accounts for their covariation (Brown, 2006). Two main FA approaches have been used in classifying personality traits. Exploratory Factor Analysis (EFA) is a data-driven process, most appropriately used when the researcher is unaware or uncertain of the relationships between the observed indicators and the underlying factors (Byrne, 2010). As the name suggests, it is mainly an exploratory tool whose main objective is to determine the optimal number of factors that represent a given multivariate data set in the absence of a theoretical basis for *a priori* specification of the factor model (Everitt & Hothorn, 2011; Hayton *et al*., 2004). Essentially, EFA is used to identify the FA of a multivariate data set, and most researchers use it in developing new assessment measures (Byrne, 2010). Studies to use EFA in the literature include De Bolle et al. (2015), Cattan (2013), Cobb-Clark & Schurer (2012), Piedmont *et al*. (2002) and Schmitt *et al*. (2007).

Confirmatory Factor Analysis (CFA) - in contrast - is theoretically grounded, appropriate when the researcher has prior knowledge of how indicators load onto factors (the factor structure) (Byrne, 2010). In CFA, the researcher specifies the number of factors, how indicators load onto the factors, and statistically tests the hypothesised factor structure (Hoyle *et al*., 2017). Specifically, the CFA model is evaluated in respect of how well it reproduces the measured variables' covariance matrix. Unlike EFA, CFA demands a strong empirical basis as a guiding block to the model specification and ultimate evaluation. In the absence of such, CFA can only be conducted after EFA has established the factor loading structure (Brown, 2006). CFA formally tests for model fit and helps establish construct validity (Brown, 2006; Revelle, 2017a). It tests how well a particular model, derived a priori, fits the data. Following other studies in the literature (Ryser, 2015; Villa & Sahn, 2015; Wortman *et al*., 2012), we use confirmatory factor analysis CFA, chiefly because the Big Five model of personality has an established factor structure for the data that we use. We justify the use of CFA on existing empirical evidence and theory, which shows that the core of Big Five factors (OCEAN) can be extracted from a set 15 trait adjectives.

2.2.3 Are the Big Five universal?

The key question for the Big Five model of measuring personality is whether it is universal across different cultures, regions, and languages. To provide an unequivocal test of the Big Five model of personality traits, studies have investigated the cross-cultural replicability of the model (McCrae & Terracciano, 2005; Terracciano & McCrae, 2006; Schmitt *et al*., 2007; De Fruyt *et al*. 2009; McCrae *et al*., 2010). Different instruments have consistently yielded the same five-factor structure that defines the Big Five personality traits (see Table 2.1). Essentially, there is a clear loading structure, with items defining a particular trait having higher loadings on that factor. In addition, the factors retained acceptable level of internal consistency and this was consistent across the sampled countries. McCrae *et al*., (2005) used translated versions of the NEO-PI-R instrument to gather

personality data in 50 countries. Using EFA, the study extracted five factors across the sample that clearly defined the OCEAN model. Schmitt *et al*. (2007), using the BFI-44, extended this research to 56 countries and used FA to extract the five factors which replicated the Big Five. In the same study, 27 countries had existing NEO-PI-R data sets, and the study uncovered significant correlations between these parallel personality instruments (BFI, NEO-PI-R) across cultures.

Interestingly, these studies also show that - across different cultures - these instruments produce distinctive patterns of the personality traits distribution that are geographically ordered. For instance, in Schmitt *et al*., 2007, African participants rated themselves low in Neuroticism while Japanese and South Koreans considered themselves less agreeable. McCrae *et al*., (2005) reports that Europeans and Americans have similar trait patterns while Asians and Africans had trait patterns that were more similar. Particularly, Africans and Asians are less extraverted than the Europeans and Americans.

Despite its success as an empirical model for identifying personality traits, the five-factor structure has not emerged everywhere. Hee (2014) used principal component analysis for Malaysian data and found a four-factor model, which excluded the Agreeableness factor. Gurven *et al*. (2013) reported a two-factor model for the Bolivian Tsimane sample. In the Bolivian sample, exploratory factor analysis using PCA failed to replicate the Big Five model, as the extracted factors subsumed items from the other four factors. Furthermore, only the first two factors showed acceptable internal consistence. Existing empirical evidence on Zimbabweans is based on small samples - mostly convenience samples (predominantly students) - and used relatively longer instruments (NEO-PI-R and BFI-44). These subsamples may not be truly representative of typical of a developing country's population. Generalising the Big Five model to the Zimbabwean population requires a more representative sample, and we address this using a heterogeneous sample of workers from different manufacturing sector industries, whose age ranges from 18 to 75 years.

2.2.4 The Big Five and individual characteristics

i) Big Five traits and gender:

Existing empirical evidence confirms pervasive patterns of gender differences in psychological dimensions (Bertrand, 2011). In respect of the Big Five personality traits, gender differences have been confirmed across cultures and can be said to be universal (De Bolle e*t al*., 2015; Schmitt *et al*., 2017; Weisberg *et al*., 2011). In the personality literature, Neuroticism and Agreeableness are the Big Five traits most consistently associated with gender differences; women score high in Neuroticism and Agreeableness on average, as compared to men (Bouchard & Loehlin 2001). The differences were evident across 50 different cultures (McCrae *et al*., 2005). In addition to this, females have been reported to score slightly higher in Extraversion and Conscientiousness than males in a longitudinal study covering 62 nations (Bleidorn *et al*., 2013). Terracciano & McCrae (2006) argued that the differences could be reflective of different forms of psychopathology that exist between females and males.

Cross-cultural research, in particular, has advanced our understanding of gender differences in personality traits. Costa *et al*. (2001), using the NEO-PI-R instrument across 26 countries (including Zimbabwe) show that the magnitude of gender differences in personality differ by culture. They report large mean differences in personality by gender for Western countries (Belgians, French, and Dutch) and little differences for developing countries (Zimbabweans and Black South Africans). Emerging evidence has shown that - in addition to culture - age has an effect on gender differences in the Big Five personality traits (De Bolle *et al*., 2015). Using cross sectional data gathered across 23 countries from school going children aged between 12 and 17 years, the study found that with increasing age, gender differences in personality traits increased in magnitude, and converged towards those reported for adults. The study, however did not find substantial variations in sex differences in personality between cultures. In the present study, we sample both female and male workers so there is a possibility for us to check for sex differences in personality traits.

ii) The Big Five and age:

Various definitions of personality traits emphasise trait stability. A large number of studies investigating the stability of traits follow work on personality in adulthood by McCrae & Costa (2008). These researchers argue that personality traits are stable in adulthood and are not seriously affected by life outcomes (Heineck & Anger, 2010; Hilger *et al.*, 2015). As a result, studies in applied settings investigating the effects of traits on economic outcomes often treat personality traits as time invariant (Anger *et al.*, 2017; Nyhus & Pons, 2012; Viinikainen & Kokko, 2012; Villa & Sahn, 2015). The assumption of stability is often a convenient one as it rules out a potential econometric problem of reverse causality. Life experiences, for instance, may shape and change individuals' traits, expectations and preferences (Cobb-Clark & Schurer, 2012).

A growing body of literature from both cross-sectional and longitudinal studies shows evidence of trait changes as individuals traverse into adulthood. The Big Five traits of Conscientiousness and Agreeableness increase, while Neuroticism decreases with age (Borghans *et al*., 2011; Soto *et al*., 2011; Bleidorn *et al*., 2013; Specht *et al*., 2014; Soto and Tackett, 2015; Kankaraš, 2017; Schwaba and Bleidorn, 2017). Two broad views, the biological and the contextual view, explain the pervasive age patterns of personality traits. The biological view argues that personality development is a genetically determined process not influenced by the environment. On the other hand, the contextual view asserts that these changes are in part influenced by environmental factors and life events (Roberts *et al*., 2008; Bleidorn, 2015; Boyce *et al*., 2015).

Increasingly, studies on personality development have shown that different forces drive specific personality changes. A longitudinal study of twin siblings reports genetic factors as strongly influencing the maturation of Agreeableness, Conscientiousness and Neuroticism, while life events induce changes in Openness to Experience and Extraversion (Bleidorn *et al*., 2009). Specht et al. (2011) report related results: genetic factors account for 40% and 57% of changes in Agreeableness

and Openness respectively. Environmental factors related to labour market dynamics have also been shown to explain trait changes. In a longitudinal study covering 8 years, employees who witnessed a job loss due to plant closures experienced an increase in the Openness trait (Anger *et al.*, 2017). A recent review of literature documents that events related to work changes, such as promotions, are related to positive changes in Conscientiousness and Openness, whereas those linked to relationships show decreases in Neuroticism (Bleidorn *et al*., 2018).

As has been consistently shown across different methodologies, personality traits change, though at different rates over one's life (Anger *et al*., 2017; Bleidorn *et al*., 2018; Pera, 2014; Roberts *et al*., 2008; Schwaba & Bleidorn, 2017). Most changes occur in early adulthood, and this marks a critical phase in the process of personality development (Briley & Tucker-Drob, 2014; Roberts *et al*., 2008; Roberts & Davis, 2016; Wortman *et al*., 2012). Recent studies applying Latent Growth Curves (LGC) report deviations in individual personality trajectories from the average population trajectory for Netherlands cohort (Schwaba & Bleidorn, 2017). Most of the heterogeneity in trait changes is amongst young adults. This, essentially, is a period of identity exploration and choices are made in respect of careers, professional qualifications and marriage.

A large body of literature in personality psychology argues that the Big Five model provides an accessible and reliable account of identifying personality traits across different cultures, religions, and languages. Different instruments have replicated the Big Five model across the world. This has not only validated the model as a human universal, but also helped build an understanding of (unobservable) human differences in behaviour. The model has been replicated amongst the Zimbabwean population; however, to date, reduced item instruments have not been tested. Our study adds to the literature by providing evidence on the adult Zimbabwean formal and informal working population. Determining personality traits allows us to investigate for sources of heterogeneity in trait patterns, particularly with respect to gender and age.

2.3 DATA

2.3.1 The MEPLMAZ Survey

The analysis draws from the MEPLMAZ survey, a longitudinal labour market survey carried out by the SALDRU at University of Cape Town. The survey uses a set of questionnaires designed to capture firm and worker data from formal and informal sector manufacturing companies across the major economic cities in Zimbabwe, over a period of two years (2015-2016). A novel characteristic of the survey central to this study is that it includes modules on participants' behavioural and psychological attributes, in addition to the demographics and socio-economic information that typically characterise national surveys. Currently, there are two waves of the survey: the first wave was conducted between July and December 2015, with the follow up wave being conducted between October and December 2016. We focus on the first wave of the survey in this chapter.

Participants were firms and employees engaged in manufacturing activities across the main industrial sectors. A stratified random sampling approach was employed, with due consideration to the location, size, and industrial sector of the firms. This gives our data the heterogeneity and representativeness that permits for a deeper analysis. In respect of location, the survey sampled employees from four main manufacturing cities. As a proportion of the sample, the majority of employees were from Harare, including surrounding areas (59.3%), and Bulawayo (32.7%). The other two locations Gweru (and Midlands) and Mutare accounted for 3.5% and 4.5% respectively.

In terms of size of firms, the study considered formal firms that employed at least five employees. In total, 195 formal firms were interviewed across the four manufacturing cities. Informal firms that formed part of the survey had at least one employee and were sampled mainly from Bulawayo and Harare. The survey included three different firm sizes, categorised based on the number of employees that a firm employed. The categories were small firms (5-19), medium (20-99), and large firms (100+), and all informal firms were categorised as micro enterprises. Table 2.2 provides the breakdown of the firms included in our survey, categorised by the location and size strata.

Table 2.2: Breakdown of firms by size and location

Location	Micro	Small	Medium	Large	Total workers
Bulawayo	40 (117)	17 (96)	23 (182)	11 (149)	544
Harare (and surrounds)	90 (183)	33 (133)	50 (338)	36 (325)	979
Mutare		2 (7)	6 (49)	2 (5)	61
Gweru (and surrounds)		9 (20)	4 (36)	2 (24)	78
Total	**130 (300)**	**61 (256)**	**83 (605)**	**51 (503)**	**1662**

NB: In parentheses is the number of workers in each firm size category, given location.

Source: Author, 2019.

Upon identifying the firms based on the firm size, industry, and location strata, employees were drawn from these firms using random sampling. For the formal firms, the target was to interview 15 workers from large firms, 10 workers from medium-sized firms and at least 5 employees from small-sized firms. The same sampling strategy was used to identify informal firm workers who participated in the survey; however, there was a variation as to the number of workers, as informal firms typically have fewer workers. The initial phase of the survey (carried out in 2015) interviewed 195 formal firms and 1 385 formal employees, and 132 informal firms and 175 informal employees. For the purpose of this study, we grouped the informal employees and self-employed together. This gave us a sample of 1 692 manufacturing sector workers.

Respondents (formal and informal workers) were administered an electronic version of a questionnaire, comprised of a number of modules on their demographic characteristics, labour market information, socio-economic indicators, personality questions, and risk and time preferences. On average, the worker questionnaire took about 15 minutes to administer, and interviews were conducted at one's workstation. An electronic questionnaire captured part of the data on informal firm owners (the self-employed), but some of the data was taken from the firm questionnaire.

2.3.2 Data descriptives

Appendix A, Table A.2 provides a summary of the sample descriptive statistics for Wave 1 of the survey, which is the focus of this chapter. Men constituted a higher proportion (81%) of the sample; a slightly higher percentage was reported in the informal sector (84%), as compared to the formal sector (80%). The married constituted 80% of the sample, the majority of these being formal sector employees (83%), compared to the informal sector (59%). The mean age for the whole sample is 40 years, though age distribution differed between the two sectors: formal sector workers are, on average older (mean = 42, SD = 11.573) than informal sector workers (mean = 33, SD = 9.554). Workers below 36 years make up 38% of the sample, 36 to 50 constitute 42%, while those above 50 make up 20% of our sample.

The data indicates that - in 2015 - most of the respondents had acquired at least some form of secondary education (75.8%) and 17.5% tertiary education. An insignificant proportion of the respondents (0.1%) had no form of formal education, while 6.64% acquired primary education by the time of the survey (Figure 2.1).

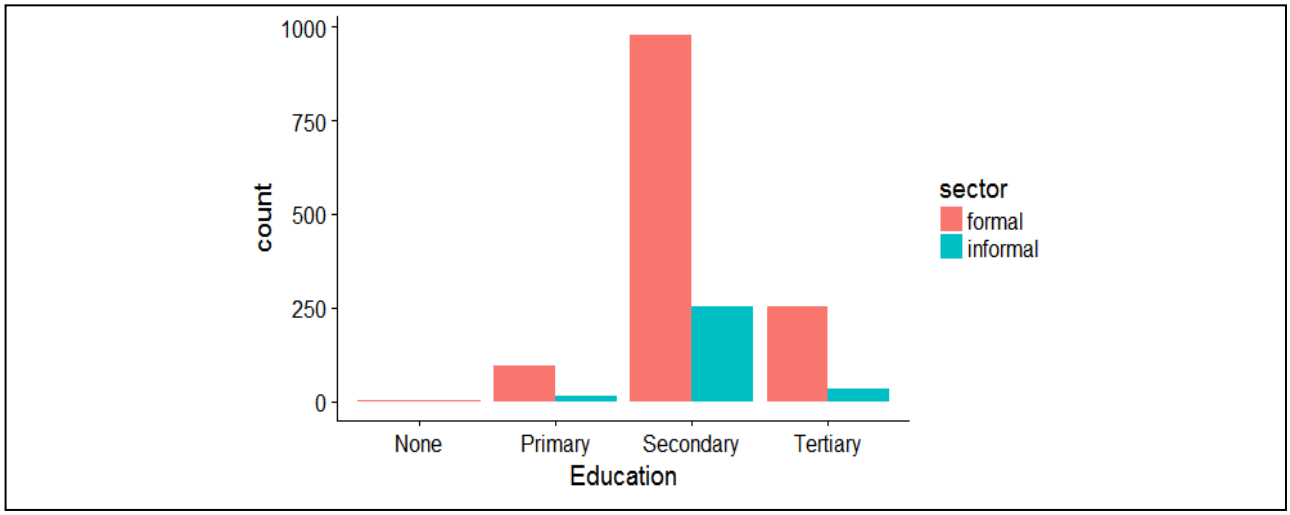

Figure 2.1: Workers education by sector of employment

Source: Author, 2019.

The data shows that workers in the Zimbabwean manufacturing sector - both in the formal and informal sectors - are relatively educated with an average number of years of formal education at 11.23 years (see Table A.2). The distribution of education by sector is almost identical, with average years of education being slightly higher for formal sector employees (11.3 Years), as compared to informal sector employees (11.1 Years). This is equivalent to Ordinary Level (O-Level) secondary education.

The data also captures information on individuals' places of birth; we are particularly interested in this variable as it gives an indication of one's ethnic group. There are main ethnic groups in Zimbabwe: the Shona and the Ndebele. However, a number of dialects exist particularly amongst

the Shona. The Shona dialects includes the Zezuru, who are mainly concentrated in Mashonaland provinces, the Karanga, mainly found in the Midlands and Masvingo provinces, as well as the Manyika who are concentrated in the Manicaland province. We use respondents' place of birth to create a variable that proxy for ethnic group.

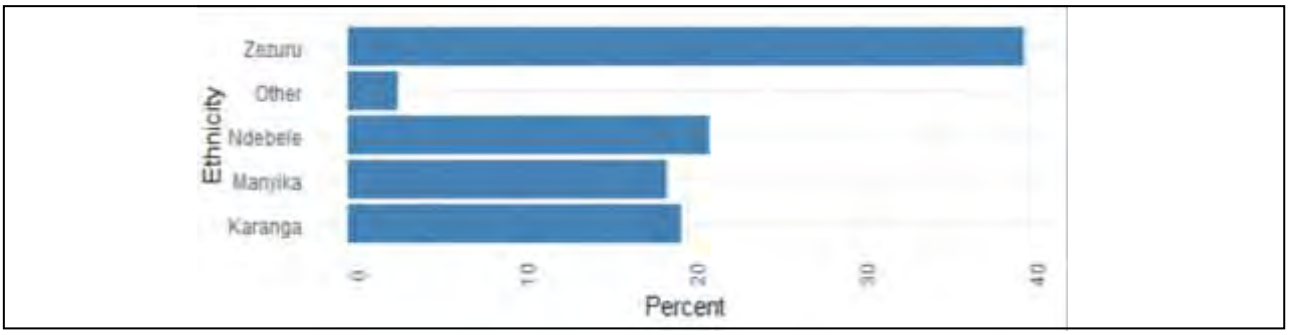

Figure 2.2: Distribution of workers by ethnic group

Source: Author, 2019.

The majority of the respondents can be classified as the Zezuru (39.9%), the Ndebele (21.3%), while the Karanga and Manyika constituted (19.8%) and 18.7% of the respondents respectively. An insignificant proportion of the workers (0.3%) were of foreign origins (represented as other in Figure 2.2). The ethnic diversity in the sample enables us to test for the hypothesis of whether differences in personality traits can be attributed to one's ethnicity.

2.3.3 Personality data

The first wave of MEPLMAZ survey, which is the focus of this chapter, included a module on individual personality traits. The module is a reduced item version of the Big Five personality inventory. It consists of a battery of 15 personality adjectives designed to capture individuals' personality traits along the five personality domains: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. The instrument was chosen to be part of survey because of its compatibility in a multi-topic survey. We refer to the reduced item instrument as the BFI-15: three items in this data set capture each of the five dimensions of the Big Five personality traits (see the instrument in Table A.3 in the appendix). The BFI-15 instrument uses a three-point rating scale (no: -1, sometimes: -3 and yes: -5), which differs from the 5-point and the 7-point Likert scales conventionally used in most instruments. The sample was administered a reduced item version of the personality questionnaire. Participants completed the reduced item version of the personality questionnaire rating how well the 15 personality traits adjectives described them. We dropped individuals with incomplete personality data, and this reduced our sample size from 1 692 to 1 666.

The descriptive statistics of the personality trait data is in Table A.3. Figure 2.3 are bar plots summarising the distribution of individual responses to the 15-trait questionnaire. The left panel shows the raw score from the data, indicating how individuals rated themselves on the 15 trait adjectives. To the right, the plots show the average scores for each of the Big Five domains. There

is an identical pattern of responses for four of the five groupings of items, specifically the Openness, Conscientiousness, Agreeableness and Neuroticism items. The pattern of how individuals rate themselves on the Extraversion items, however, is not uniform. Based on the averages, our data suggests that workers score high in Agreeableness, Openness to Experience and Conscientiousness; they score low, however, on the Neuroticism variable.

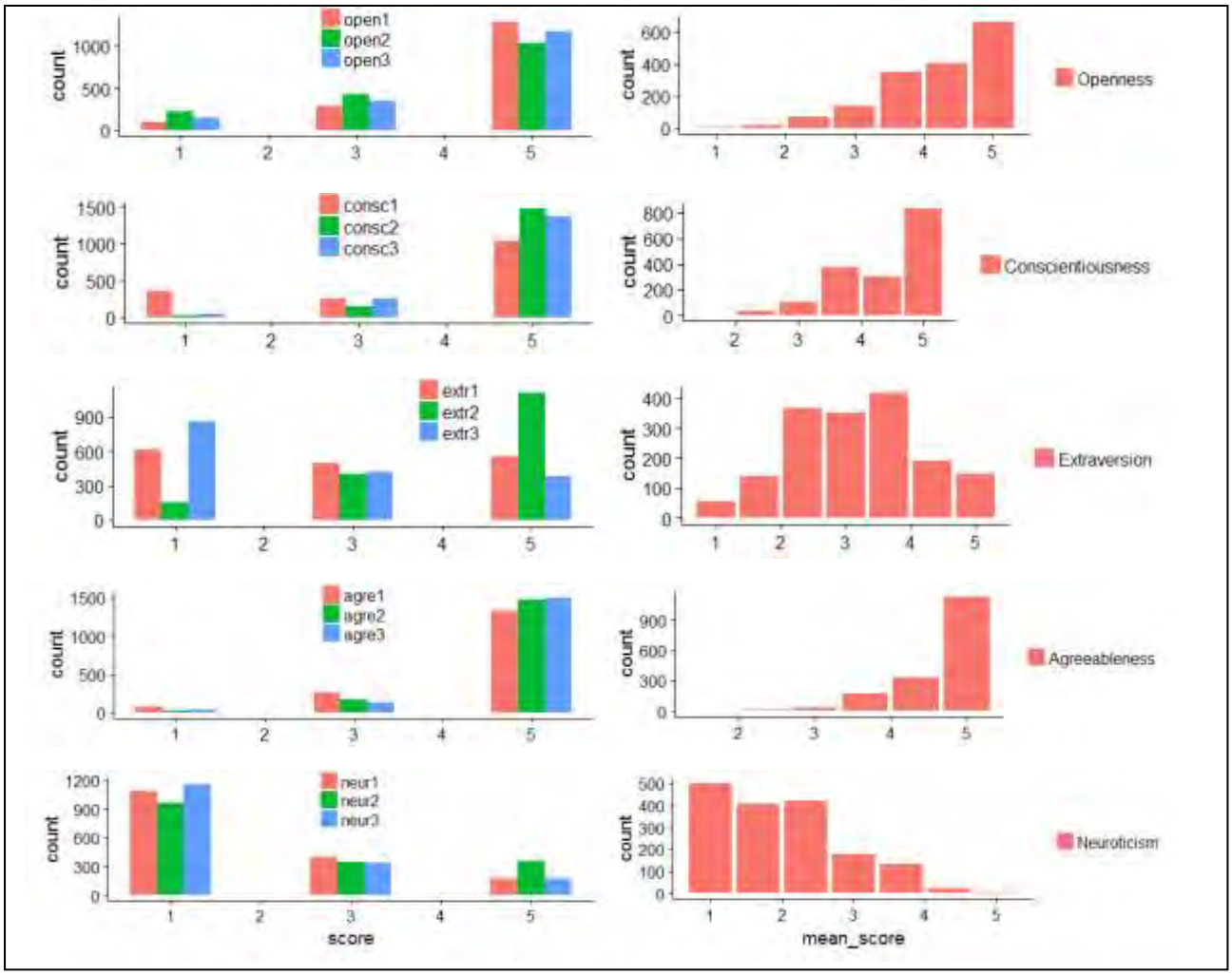

Figure 2.3: Questionnaire scores (and averages) for the sample

Source: Author, 2019.

As argued in the literature review, the average trait scores may not give a reliable account of individual personality, chiefly because of the restrictive assumption that each of the items carries the same weight in explaining the factors. We take mean scores as suggestive of participants' overall trait orientation. To identify factors that account for variability in our multivariate data, we utilise factor analytic methods.

2.4 DETERMINING PERSONALITY TRAITS

2.4.1 Estimating Personality Traits

Before conducting factor analysis (FA), the study examines if the data meets the minimum acceptable criteria for FA using the Kaiser-Meyer-Olkin (KMO) test. The KMO test gauges the suitability of our personality data for FA. It indicates the degree to which each variable in a set is predicted without error by the other variables. It estimates the overall measure of sampling adequacy for the personality data, as well as estimates for each of the 15 personality items. We calculate this measure using the *KMO( )* function in the Psych package (version 1.7.5) of R (Revelle, 2017). A value of zero indicates that the sum of partial correlations is large relative to the sum correlations, indicating factor analysis is likely to be inappropriate. A value close to one indicates that the sum of partial correlations is not large relative to the sum of correlations and so factor analysis should yield distinct and reliable factors. We report an overall measure of sampling adequacy (MSA) of 0.66. Each of the fifteen items that constitute our data - except for two (0.58 and 0.59) - had an MSA statistic above 0.6 (see Table A.3). The ideal value should be at least 0.6 (Williams *et al*., 2010); however, any value above 0.5 is reasonably adequate (Hee, 2014). This result suggests that we can extract distinct and reliable factors from our personality data using FA.

In this paper, we follow previous literature in the field (Ryser, 2015; Villa & Sahn, 2015; Wortman *et al*., 2012) and use factor to create indexes that define individual personality traits. We employ CFA and model the Big Five as unobservable latent variables. As discussed earlier, CFA analysis is a reliable way to estimate the five personality traits, since there is an established factor loading structure for the existing validated personality instruments. Furthermore, there is a solid theoretical and empirical backing for the Big Five model, and the model has successfully yielded the same results across cultures, languages, and regions. Specifically, cross cultural studies using different instruments have successfully yielded the same five-factor structure (Schmitt *et al*., 2007; McCrae *et al*., 2010; Bleidorn *et al*., 2013). We follow the approach by Villa & Sahn (2015) in the literature, and use test item scores to estimate the following structural equation model:

$$
\begin{aligned}
z_j^O &= \mu_j^O + \lambda_j^O \theta^O + \varepsilon_j^O \quad for\ j \epsilon \{1 \dots, m_j^O\} \\
z_j^C &= \mu_j^C + \lambda_j^C \theta^C + \varepsilon_j^C \ for\ j \epsilon \ \{1 \dots, m_j^C\} \\
z_j^E &= \mu_j^E + \lambda_j^E \theta^E + \varepsilon_j^E \quad for\ j \epsilon \{1 \dots, m_j^E\} \\
z_j^A &= \mu_j^A + \lambda_j^A \theta^A + \varepsilon_j^A \ for\ j \epsilon \ \{1 \dots, m_j^A\} \\
z_j^N &= \mu_j^N + \lambda_j^N \theta^N + \varepsilon_j^N \quad for\ j \epsilon \{1 \dots, m_j^N\} \qquad (2.1)
\end{aligned}
$$

where O, C, E, A, and N represent the Big Five dimensions of Openness to Experience, Conscientiousness, Agreeableness, Extraversion and Neuroticism respectively. We define z_j^P as the latent variable measuring individual j's personality traits P for $P \epsilon \{O, C, E, A, N\}$. The θ^P represents the 3-items that measure each of the Big Five personality traits P in our personality data. The ε's are assumed to have a mean of zero, are uncorrelated with the factors and are independent

across individuals and factors. We use the structural equation model above to estimate the factor loadings (λ_j^p). The factor loadings are used to predict an individual's personality trait score for the entire sample.

We estimate the model in R using the Lavaan package (Rosseel, 2012). Specifically, we rely on the *cfa( )* dedicated function in lavaan to fit the confirmatory factor model defined by Equation 2.1. We specify the factor model in which three items are indicators of each of the five factors as defined by the above system of equations, and fit the model in R (R core, 2017) using the Maximum Likelihood estimation method. As standard practice in many social sciences, we standardise[7] the latent factor score that represents individual personality traits (Villa & Sahn, 2015).

2.4.2 Confirmatory factor analysis

i) Empirical Model (CFA Model 1):

Following the description in the previous section, we use CFA to test for a five-factor model of personality traits using data from the MEPLMAZ survey. Our analysis follows previous research which confirmed that a five-factor structure can be used to meaningfully and sufficiently define personality traits (McCrae & John, 1992; Schmitt *et al*., 2007; Villa & Sahn, 2015; Wortman *et al*., 2012). Using the measurement model specified in equation 2.1, we fit a confirmatory factor model (CFA Model 1) with the 15-items, as input to the equation, and test for the Big Five model of personality. We use lavaan version 0.5-23.1097 (Rosseel, 2017) in R version 3.4.2 (R core, 2017), for our analysis. In the lavaan package, we use the *cfa( )* function to fit the five-factor three-indicator model that we specified in equation 2.1, using the Maximum Likelihood technique (Revelle, 2017a). In the *cfa( )* function, we specify that the latent variables should be standardised, which permits free estimation of all factor loadings (Rosseel, 2017; Rosseel *et al*., 2017). CFA tests whether the data fits the Big Five measurement model. We constrain each of the three indicators to load exclusively on the hypothesised factor that it measures (Williams *et al*., 2010) and estimate a confirmatory factor model as outlined in the previous section.

Table A.4 gives a summary of the main measures of model fit. In deciding model fit, studies typically rely on a number of fit indices: primarily Chi-square, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) and the Standardised Root Mean Square Residual (SRMR). Using a number of fit measures is of importance, as it ensures that the Chi-square is not influenced by sample size (Miller *et al*., 2015; Revelle, 2017). The threshold for model acceptability are values below 0.05 for both the RMSEA and SRMR, and above 0.9 for the CFI (Hu & Bentler, 1999; Topolewska *et al*., 2014). We evaluate model fit based on these measures. The study reports a Chi-square = 742.15 (df =80) and $p < 0.000$, RMSEA = 0.07, CFI = 0.672 and SRMR = 0.064, indicating

[7] Standardising factor scores allows free estimation of all factor loadings, and constraints the latent factors to have a mean of zero and a variance of one. We do this by setting std.lv = TRUE when calling the cfa( ) function.

that model fit is poor. Based on these evaluation criteria, the empirical model fails to pass fit and cannot be used to fit our multivariate personality data.

ii) Modifying the confirmatory model:

The main question that arises from our results is why the empirical-based model fails to fit our personality data. In literature, there are a number of possible sources of failure of model fit, and accounting for these factors may help improve model fit (John and Srivastava, 1999; Topolewska *et al*., 2014). We examine the latent factor matrix of our results (CFA Model 1), and found that some items have relatively low factor loadings on the latent variables. Specifically three items, one from the Agreeableness (agre3), one from the Conscientious (consc1) and one from the Neuroticism (neur1) factors, had low factor loadings as indicated by low standardised regression coefficients (see Table A.4). Two of these items (cosnc1 and neur1) were negatively worded in the questionnaire; this may have undermined their psychometric properties (Ryser, 2015).

We examined if there are any other relationships that may exist between items in the specified model using modification indices (Table A.5). Modification indices (MI) sorted from highest to lowest, indicate how model fit would improve if new parameters were added to the model[8]. We consider the relationships that produce the highest MI, and our results suggested covariance between some of the item tests, particularly consc2 and open1, which have the highest MI. Other variables that covary are agre2 and consc3, as well as extr2 and neur2. The existence of covariance between test items from different factors is not peculiar in the social sciences; personality studies, for instance, have reported item cross loading, a scenario where an item loads onto more than one factor (DeYoung, 2006; Gurven *et al*., 2013). We consider the items that have the highest covariance between them in the modified confirmatory factor model. This is in line with the literature; one can correlate a pair of errors in the model to improve model fitness (Topolewska *et al*., 2014). Our modified model excludes the three items that had low factor loadings, but includes correlated errors as suggested by modification indices.

iii) Modified Model (CFA Model 2):

Using the same estimation procedure as before, we fit the modified confirmatory factor model in R, and test if the model explains the personality data using the maximum likelihood technique (Table A.6). The modified model has two-items, each defining O, C, A and N, and retains the three-items for E. In addition, we include items whose error terms are correlated; specifically, we specify covariance between consc2 and open1, agre2 and consc3, as well as extr2 and neur2 (as suggested by the MI). We are particularly interested in three main measures: the CFA, RMSEA and SRMR. The model fit indices improve significantly; we report a chi-square of 80.95, and a CFI of 0.96 that is above the minimum threshold of 95%. The RMSEA and the SRMR are both below the conventional

[8] http://www.understandingdata.net/2017/03/22/cfa-in-lavaan/

fit levels of 5% (Table 2.3). The modified confirmatory factor model fits the data better as compared to the empirical factor model that did not allow for covariance amongst the test items. As expected, all the items (indicators) had significant factor loadings. Figure A.1 in the appendices gives a diagrammatic representation of the confirmatory factor model structure, which shows the respective indicators and the factors on which they load.

Table 2.3: Fit measures for CFA models

Measures	chisq	df	CFI	RMSEA	SRMR
CFA model 1	742.152	80	0.672	0.07	0.064
CFA Model 2	80.952	31	0.963	0.03	0.027

Source: Author, 2019.

We use the modified confirmatory factor model (CFA Model 2) to predict personality trait scores for each individual, as an unobservable latent variable in R. In particular, we use the lavPredict function in the lavaan package to predict standardised factor scores that explain our personality data, for each individual with complete personality data. The predicted five factors scores (OCEAN) define the latent variables that influence the indicator variables and account for their correlation.

2.4.3 Dedicating measurements to factors and interpreting factors

Short instruments have been shown to possess the psychometric properties to measure the core Big Five personality traits (Gosling *et al*., 2003; Rammstedt & John, 2007). This, however, comes at a cost, as the short instruments cannot adequately capture all the facets that define the Big Five model. In interpreting the extracted factors, it is thus necessary to define the extracted measures in respect of the items that load on each factor. When compared to other instruments, for instance the 240-item NEO-PI-R (Costa & McCrae, 2008), it is evident that our instrument could only capture a few facets that are (theoretically) highly correlated to the Big Five dimensions. Hence, the personality measures extracted approximate the Big Five personality traits. They represent lower order factors that measure facets of the Big Five personality dimensions.

The agreeableness factor measures one's tendency towards interest in people and caring for other people's problem. The factor captures items measuring the altruism facets of Agreeableness. The Neuroticism factor consists of two items that identify with the Neuroticism facet of angry hostility. The factor defines one's tendency towards irritability (easily angered) and constantly encountering mood swings. The Extraversion factor describes one's tendency towards being sociable and showing interest in people, characteristics that define the gregariousness facet of Extraversion. The Conscientiousness factor captures one's orientation towards paying attention to detail, and adherence to completing given tasks right away. The items define the self-discipline facet of Conscientiousness. The Openness to Experience factor is defined by two items that capture one's tendency of being creative and full of ideas, items that measure the Openness to ideas facet.

2.4.4 Internal reliability

We investigate the internal reliability of the personality trait measures using the standardised Cronbach's alpha reliability index. In the Psych package of R, there is an *alpha( )* function dedicated to calculate the coefficient alphas for latent factors (Revelle, 2017a). The index developed by Lee Cronbach in 1951 assesses measurement error problems; in particular, whether the items that form a factor indeed measures the same construct. The study reports an overall Cronbach alpha of 0.79: all five factors except one (Extraversion - 0.65) had alpha reliabilities satisfying the conventional cut-off of 0.7 (see Appendix A, Table A.7). Specifically, Agreeableness, Conscientiousness, Openness and Neuroticism had Cronbach's alphas of 0.70, 0.73, 0.7, and 0.9 respectively. These results are comparable to those reported in the literature; for instance, the lowest alpha coefficient reported for the Zimbabwean population was 0.68 (Piedmont *et al*., 2002). Wortman *et al.* (2012) found low Cronbach alpha for Openness (0.66) but all the other factors returned reliability coefficients above 0.77. Studies using reduced item instruments in the literature also reported Cronbach alphas above 0.7 (Rammstedt & John, 2007; Schmitt *et al*., 2007; Viinikainen & Kokko, 2012).

2.4.5 Conceptualising personality measures

We can safely say that the measures give us a reliable account of individual personality traits. We found evidence that our personality data fits a five-factor structure that reflects the Big Five model. There is evidence of correlations among our personality trait measures; agreeable individuals, for instance, are more likely to be conscientious, extraverted and open, but less likely to be neurotic. Taken together, the results show consistency with findings in literature on the characterisation of personality traits as comprising five distinct factors (OCEAN) (Villa & Sahn, 2015).

Despite this, there are a number of weaknesses related to our study, which may explain why the empirical confirmatory model failed to fit our data. The first is that the instrument may not capture all the personality domains. The trait adjectives used in the study do not sufficiently capture all the facets of the Big Five model, an aspect related to adequacy of the instrument in capturing all the facets of the Big Five traits. The instrument used a three-point rating scale, which differs from the five- and seven-point scales used in other studies. In addition, it is an English version. Despite acquiring an average of 11 years of education, it is possible that the respondents failed to comprehend the questions well. Piedmont *et al*. (2001) cites the lack of proper Shona terms that describe the equivalent of some of the English personality terms.

A second possible reason relates to the individual response styles and biases. The sizeable correlations amongst the factors is suggestive of this. This may be reflective of how Zimbabweans tend to assess themselves, for example the tendency towards socially desirable responding (rating oneself highly in Agreeableness and Conscientiousness, and low in Neuroticism). This may introduce error in the measurement of constructs (Piedmont *et al*., 2002). Given the conservative nature of Shona culture for instance, and less familiarity to personality questions of the respondents,

it is possible that respondents were uncomfortable reflecting their self-ratings for items perceived to be negative.

2.5 DISTRIBUTION OF PERSONALITY TRAITS

As the next step in the study, we map the differences in workers personality traits across the sample. We offer a comprehensive examination of the extent to which workers' personalities differ across a number of individual characteristics, including their geographical location. We test for differences in the distribution of the personality using the Kolmogorov-Smirnov tests, and use density plots to visualise the differences in the distribution. The study ran regression equations with demographic characteristics as covariates. This examination deepens our understanding of the factors that explain heterogeneity in personality traits amongst workers. This, particularly, may help improve our understanding of the observed differences in employment outcomes in an environment of economic uncertainty.

2.5.1 Personality trait density plots

The density plots provide a map of the smoothed distribution of personality traits from the CFA model (Figure 2.4). The peaks indicate the area of highest concentration of the trait scores and, in particular, the higher the score the stronger the average participant's orientation towards a given personality attribute.

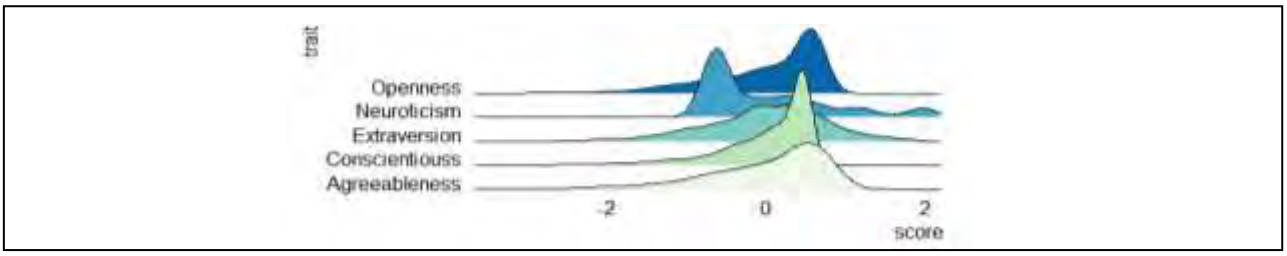

Figure 2.4: Density Plot of personality trait scores

Source: Author, 2019.

A quick glance at the density plot suggests that, on average, participants score high in Openness to Experience, Agreeableness, and Conscientiousness, while scoring low in Neuroticism (Figure 2.4). There is an even distribution in the personality trait scale of Extraversion.

2.5.2 Personality traits and demographic characteristics

Following empirical literature documenting differences in distribution of personality traits by demographic and geographical factors, the study investigates if there are differences in personality traits by age, gender, ethnicity, and location. We do this by running first stage regressions of each of these variables – separately - on the five-personality trait variables extracted from the modified CFA model. The study disaggregates the distribution of personality traits by gender, age group, ethnicity and geographical location.

i) Gender and personality traits:

The understanding of gender differences in personality traits is important to our understanding of human variation (Weisberg *et al*., 2011) and gender differences in economic success (Antecol & Cobb-clark, 2013; Nikolaou, 2012; Nyhus & Pons, 2012). We test for gender differences in personality traits using the Kolmogorov-Smirnov tests in R. For all the five factors, the test rejects the hypothesis of equality of personality distributions between male and female. We found p-values of less than 0.001 for all the five trait variables, confirming significant statistical differences in the distribution of personality traits by gender. We regress gender on the five personality traits. Table 2.4 gives a summary of the results. On average, male workers score more in Openness, Conscientiousness, Agreeableness and Extraversion, compared to their female peers who score high in Neuroticism (see Appendix A, Figure A.2 for plots). The results are consistent with earlier findings on gender differences in personality reported in literature (Soto *et al*., 2011; Soto and Tackett, 2015). The findings, however, contradict findings in literature in respect of the Agreeableness factor, which reports higher agreeable values for females than males. The unexpected sign may reflect the inadequacy of our instrument in capturing all the facets that define this factor. Overall, the results suggest that our measures reproduce related correlations with the gender variable; this gives us confidence that our five factors are related to the Big Five constructs.

Table 2.4: Personality traits and gender

	Agreeableness	**Conscientiousness**	**Extraversion**	**Neuroticism**	**Openness**
male	0.205***	0.132***	0.066	-0.213***	0.204***
	(0.047)	(0.039)	(0.047)	(0.049)	(0.045)
R^2	0.011	0.007	0.001	0.011	0.012

****p<0.01, **p<0.05, *p<0.1*

Source: Author, 2019.

ii) Age and personality traits:

We investigate the age differences in personality traits. First, we regress age and its square on the five traits. We found statistical evidence confirming correlations between age and all of the personality trait variables - except for Neuroticism - which is statistically insignificant (Table 2.5). The findings confirm the age variant development process of personality traits. Cobb-Clark & Tan (2011) argued that - in estimating effects of traits on economic outcomes - there is need to account for age.

Table 2.5: Personality traits and age

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
age	0.022***	0.016*	0.024**	0.005	0.012***
	(0.010)	(0.008)	(0.010)	(0.010)	(0.004)
agesqr	-0.262**	-0.170*	-0.300***	-0.071	-0.119***
	(0.116)	(0.097)	(0.115)	(0.122)	(0.046)
R^2	0.003	0.003	0.005	0.000	0.007

****p<0.01, **p<0.05, *p<0.1*

Source: Author, 2019.

We further the analysis by investigating the cross sectional age trends of personality, using a categorical variable capturing the three age groups. This analysis follows literature documenting differences in personality traits between emerging adulthood, adulthood and late adulthood (Bleidorn *et a*l., 2013; Schwaba & Bleidorn, 2017). Results shows little statistical evidence between age groups and personality traits, except for the Conscientiousness trait (Table 2.6). Adult respondents, on average, are more conscientious compared to the emerging adult population group; this relationship is, however, insignificant in respect of the late adulthood group but returns the expected sign (Cobb-Clark & Schurer, 2012; Wortman *et al*., 2012; Schwaba & Bleidorn, 2017). Piedmont *et al*. (2002) reported the same result for Zimbabwe, specifically in relationship to Conscientiousness, Agreeableness and Neuroticism. Overall, despite being insignificant, the correlations between age group variables and personality traits carry the anticipated signs. For instance, personality development literature has consistently reported Neuroticism declining and Agreeableness increasing with age (Soto *et al*., 2011; Specht *et al*., 2011, 2014).

Table 2.6: Personality traits and age group

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
36 to 50	0.067	0.090***	0.025	-0.037	0.039
	(0.042)	(0.035)	(0.025)	(0.044)	(0.039)
Above 50	-0.053	-0.026	-0.074	-0.017	-0.068
	(0.052)	(0.043)	(0.051)	(0.054)	(0.049)
R^2	0.004	0.004	0.002	0.000	0.003

****p<0.01, **p<0.05, *p<0.1*

Source: Author, 2019.

iii) Ethnicity and personality trait:

We test for trait differences by ethnicity, using Zezuru as the base. Amongst the five ethnic groupings, our results show significant trait differences between the Shona Zezuru and Ndebele across all the five traits (Table 2.7). On average, the Ndebele rate themselves less in Agreeableness, Conscientiousness, Extraversion and Openness to Experience, while the Zezuru rate themselves as less neurotic. There is limited evidence of intra-ethnic differences amongst the Shona dialects, and the relationships are weakly significant; specifically, the Zezuru score lower in Neuroticism than the Karanga, and the Manyika are less open to experience than the Zezuru (see Figure A.2 plots).

Table 2.7: Personality traits and ethnicity

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
Ndebele	-0.274***	-0.226***	-0.157***	0.087*	-0.133***
	(0.049)	(0.041)	(0.049)	(0.052)	(0.047)
Manyika	-0.077	-0.041	-0.041	0.059	-0.093*
	(0.052)	(0.043)	(0.052)	(0.055)	(0.049)
Karanga	-0.007	0.006	0.057	0.101*	0.009
	(0.051)	(0.042)	(0.051)	(0.101)	(0.048)
Foreigners	-0.461	-0.326	-0.252	0.324	-0.563*
	(0.338)	(0.281)	(0.337)	(0.357)	(0.322)
R^2	0.021	0.021	0.010	0.003	0.008

****p<0.01, **p<0.05, *p<0.1*

Source: Author, 2019.

iv) Geographical location and personality traits:

We use Harare as the base to test for personality trait differences by location. On average, Bulawayo workers are more extraverted and neurotic than those employed in Harare firms (Table 2.8). Mutare workers, on average, score less in all of the five personality factors, except for Neuroticism, the only trait they score higher when compared to Harare workers. These differences suggest geographical differences in individual personality traits.

Table 2.8: Personality traits and geographic location

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
Bulawayo	-0.008	-0.046	0.066*	0.089**	0.024
	(0.040)	(0.033)	(0.040)	(0.042)	(0.037)
Gweru	0.076	0.116	-0.026	-0.150	0.084
	(0.101)	(0.084)	(0.100)	(0.107)	(0.094)
Mutare	-0.707***	-0.559***	-0.531***	0.186*	-0.832***
	(0.089)	(0.074)	(0.089)	(0.095)	(0.083)
R^2	0.038	0.035	0.025	0.006	0.060

****p<0.01, **p<0.05, *p<0.1*

Source: Author, 2019.

We combine the demographic variables in a single regression and include sector of employment (Appendix A, Table A.8). All the other variables retain relatively similar results. Interestingly, in respect of the sector variable, informal sector employees on average score high in Openness to Experience, compared to their formal sector peers, that being the only significant relationship. This result may be suggestive of the influence of environmental factors in shaping personality development. Literature on the effect of labour market experiences on personality development supports this; for instance, labour market shocks - particularly a loss of job followed by an extended unemployment duration and subsequent reemployment - were found to increase one's Openness to Experience (Anger *et al*., 2017; Bleidorn *et al*., 2018).

Overall, the results show that there is heterogeneity in workers personality profiles explained by age, gender, ethnicity, and location. We report significant correlations between the personality trait measures and individuals' demographic characteristics. The findings confirm long-standing empirical findings reported in literature, for instance differences in traits by gender and age (Schwaba & Bleidorn, 2017; Soto *et al*., 2011; Soto & Tackett, 2015; Wortman *et al*., 2012).

2.6 CONCLUSION

The aim of study was to estimate individual personality traits using a reduced item instrument. We apply CFA to a novel data set from a representative sample of Zimbabwean manufacturing sector workers, to extend research on the Big Five model within a developing country context. We justify use of CFA on the already established factor structure of the Big Five, which has theoretical and empirical backing in personality psychology. We tested for the Big Five model using our 15-item data, and model fit was poor. We considered modification indices, and re-specified our factor model by dropping items with low factor loadings. The modified confirmatory factor model passes fit and is used to estimate individual personality traits. The model extracts five factors, which identify with the Big Five model OCEAN. These factors proxy the Big Five, specifically lower order facets that are highly correlated with the Big Five personality traits. Our personality constructs show acceptable levels of internal consistency, with an overall Cronbach alpha of 0.79, which is comparable to what other studies report. Furthermore, the correlations between our personality trait measures follow patterns reported in literature, with Neuroticism negatively related to all the other factors.

The chapter compliments existing literature and expands on studies in developing countries, especially on the usage of reduced item instruments in determining personality traits. It offers insights on the sources of individual differences other than the observable human capital variables. We report differences in personality traits by gender, age, geography, and ethnicity. However, due to the cross-sectional nature of our data, we could not formally test for the factors that explain personality trait development over time. There is no doubt that individual worker's experiences in the labour market may shape personality development, more so in an environment characterised by uncertainty; however to empirically test for this requires longitudinal data. This limitation implies that in controlling for personality traits in estimating their effect on economic outcomes, we treat them as stable following other studies in the literature (Nyhus & Pons, 2009, 2012; Villa & Sahn, 2015).

At the practical level, the study provides an important first step towards understanding unobservable individual heterogeneity. Future research can profit from relating the computed measures to socio-economic indicators. In particular, given the richness of our data set, we can further research on the effect of individual differences in personality on labour market outcomes. However, there is need for caution in interpreting the traits, as they do not capture all the aspects that define the Big Five traits; we rather interpret them as lower order facets of the Big Five.

CHAPTER 3

PERSONALITY TRAITS AND LABOUR MARKET OUTCOMES IN ZIMBABWE

ABSTRACT

Growing evidence in economics links personality traits to individuals' life outcomes. However, there is little empirical evidence examining the effects of these traits on labour market outcomes in developing country contexts. This study uses a novel matched employer-employee data set from Zimbabwe's manufacturing sector (formal and informal) to examine the relationship between personality traits and individuals' labour market outcomes. We estimate standard economic models on sectoral selection, earnings, and employee mobility, and control for unobservable individual heterogeneity in personality traits using the Big Five personality model. In both models, we find evidence of the significance of personality traits in explaining manufacturing employment outcomes. Personality traits influence earnings through two potential channels; directly through influencing productivity and indirectly via occupational choice. In respect of job mobility, significant interaction effects between personality traits and employment shocks suggest that - depending on firm specific experiences - personality traits help shape individuals mobility decisions. This study contributes to the literature in the context of a developing country characterised by economic uncertainty, by integrating insights from personality psychology into mainstream economic models that investigate labour market outcomes.

Keywords: personality traits, big five, earnings, employee mobility, labour market outcomes.

3.1 INTRODUCTION

Until recently, literature on labour market outcomes largely recognised human capital variables such as cognitive skills, education, experience, and training as central in explaining observed differences in levels of economic success. However, significant portions of variations in individual labour market outcomes remain unexplained, even within a given range of human capital and demographic characteristics (Heckman *et al*., 2006). Economists lately focused on non-cognitive skills, which emerged as a strong candidate in explaining the residual. Amongst a set of non-cognitive skills[9], personality traits – and the Big Five in particular - are the most relevant instrument in studying economic outcomes. The Big Five has been shown to predict a number of labour market outcomes, including sectoral choice, earnings, job mobility, job satisfaction, and occupational status (Almulund *et a*l., 2011; Bowles *et al*., 2001; Brunello & Schlotter, 2011; Dohmen, 2014b; Heckman & Kautz,

[9] Other measures of non-cognitive skills used in analysing economic outcomes include self-esteem and internal locus of control (Heckman *et al.*, 2006).

2012). The literature so far has concentrated on developed countries[10]. It is however, conceivable that - given the structural economic differences between developed and developing countries' labour markets - mechanisms through which personality traits explain economic success may differ. For instance, precise execution of tasks and industriousness (Conscientiousness) may be considered valuable and thus rewarded more in developing countries, compared to skills that are linked to intellectual curiosity (Openness to Experience) which may be more valued in developed countries.

The absence of appropriate data and methods to capture personality traits particularly constrained research in this area, especially for developing countries. Using a novel matched employer-employee survey data set from Zimbabwe; we contribute to the body of work by examining the relationship between personality traits and labour market outcomes within a developing country context. The survey provides detailed information on individual personality traits and labour market outcomes, for a nationally representative sample of formal and informal sector manufacturing firms and employees. The two-wave survey allows us to carry out both a static and dynamic analysis of individuals' labour market outcomes. Unlike most studies that focus on earnings, we provide (in addition) an integrated analysis on how personality traits explain individuals' sectoral choices and mobility patterns. Most importantly, we account for endogenous sectoral selection in the earnings equation, thus capturing both the direct and indirect effects of personality on earnings.

Labour market earnings constitute the main source of income for a majority of households in developing countries; it is thus imperative to understand which attributes contribute to labour market success. In an economic environment characterised by uncertainty, personality traits may be an important aspect in the economic decision making matrix, as individuals weigh alternative strategies to maximise incomes. In particular, empirical evidence shows that, under stressful situations, copying mechanisms adopted by individuals are in part a function of their personality dispositions (Hambrick & McCord, 2010; Nieß & Zacher, 2015; Straud *et al*., 2015). Individuals high in conscientious and Openness to Experience - for instance - are more likely to identify future stressful situations and develop copying mechanisms in advance.

Focusing on Zimbabwe offers a new perspective given its unique features: a developing country with a fragmented labour market whose economy is characterised by uncertainty. While most of the existing literature focuses on formal employment, this study extends the analysis to the informal sector and simultaneous analyses of individuals' outcomes across different industrial sectors. Through this study, we are able to glean answers to the seemingly difficult but important questions in the field of labour economics. In particular, we contribute to the discussion on the relation between personality traits and labour market outcomes in developing countries by focusing on the following questions:

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[10] Few studies have examined the effect of personality traits on developing country labour markets (Glewwe *et al.*, 2017; Hilger *et al.*, 2015) and only one considers the informal sector (Villa & Sahn, 2015).

i) How important are personality traits in explaining individuals' sectoral selection?

ii) Do personality traits explain earnings?

iii) What is the effect of personality traits on employee mobility patterns?

Such an integrated analysis brings insights into the traits that define success across different states of employment within a developing country context.

Our analysis follows the basic approach of estimating standard labour market models of sectoral choice, earnings, and mobility. The main innovation we incorporate is unobservable individual heterogeneity in the form of personality traits, in each of these models. We use standardised measures of the Big Five personality traits derived from a reduced item instrument using CFA. Since our sample consists of individuals from two main sectors (informal and formal), we begin our analysis by modelling occupational selection using a multinomial logit approach. We consider three main occupational categories: formal employment, self-employment, and informal employment, which are mutually exclusive. Then, correcting for the endogeneity of personality in occupational selection in the fashion of Durbin & McFadden (1984), we estimate the relationship between personality traits and earnings. Using second wave survey data, we extend our analysis and explore the dynamic aspects relating to workers' transitioning from one labour market state to another. Specifically, we examine the link between personality traits, past employment shocks and employee mobility, using probit and multinomial logit models. We disentangle the reasons behind external mobility and further investigate if they relate to personality traits.

Our results show that personality traits explain individuals' sectoral selection, an indirect channel through which they also affect labour market returns. Individuals who score high in Openness to Experience, Agreeableness and Neuroticism are more likely to be involved in informal sector activities (self-employment and informal employment) relative to formal sector employment. On the contrary, high scores in Conscientiousness and Extraversion are associated with a higher likelihood of formal employment, relative to informal sector activities. In respect of earnings, the augmented Mincer equation results suggest that endogenous sectoral selection is important in explaining earnings differentials. Personality traits further have limited direct effect on earnings after correcting for initial sectoral selection. However, the returns to personality traits differ, depending on one's sector of employment. Significant interaction effects between traits and sector of employment support this. The traditional human capital variables - education and experience - return their expected signs, signalling their importance in explaining individual earnings differentials.

Our estimates of mobility show that personality traits explain individuals' mobility patterns. Significant interactions effects between personality traits and employment shocks suggest that the effects of personality traits on mobility evolve with shocks. Highly conscientious and agreeable workers, employed in firms that experienced an employment shock, are more likely to move compared to the same individuals working in firms that did not experience a shock. Estimates of the fixed effects

probit model, however, suggests that unobservable firm specific heterogeneity is important in explaining mobility. The Big Five personality traits enter insignificantly into the firm fixed effects model. Multinomial logit models on the nature of mobility show that employment shocks explain involuntary separation due to company closures, while education and gender explain voluntary mobility. In respect of the Big Five personality traits, individuals who score high in Neuroticism are more likely to encounter involuntary separation in the form of closed firms, and are less likely to be targets of retrenchments.

The study progresses as follows. In the next section, we discuss the empirical literature on the link between personality traits and labour market outcomes. In particular, we explore how personality traits explain individuals' sectoral selection, earnings and job mobility behaviour. In Section 3.3, we describe our empirical approach and the data. Section 3.4 presents results of our labour market models, estimated for a sample of Zimbabwean manufacturing sector workers. The Chapter concludes and discusses the implications of our findings in the last section.

3.2 EXISTING EMPIRICAL WORK

Long-standing literature exists in the economics discipline, investigating the foundation and mechanisms of differences in individuals' labour market outcomes. Two main views emerged. The older one holds that cognitive skills (for instance IQ, intelligence, test scores etc.) and human capital variables are the main determinants of success in the labour market. The other view, the most recent, argues that non-cognitive skills - also referred to as personality traits (such as motivation, persistence, leadership, and social skills) - are at least as important as cognitive skills in influencing success (Almulund *et al*., 2011; Brunello & Schlotter, 2011). There is emerging consensus that accounting for unobservable heterogeneity in personality traits expands our understanding of how individuals with seemingly similar human capital endowments may achieve varying levels of labour market success.

3.2.1 The Big Five Model

Economists have only recently given attention to the so-called non-cognitive skills. While extremely important in explaining economics outcomes, cognitive skills fail to fully account for observed variations in levels of economic success (Cunha *et al*., 2006; Heckman & Kautz, 2012; Heineck & Anger, 2010; Villa & Sahn, 2015). Early studies utilised measures such as self-esteem and feelings of self-efficacy; these have, however, been shown to suffer from endogeneity (Cubel *et al*., 2016). Extended unemployment spells, for instance, negatively affect one's self-esteem. Economists and psychologists lately focussed on the Five Factor model of personality (Costa & McCrae, 1992), commonly referred to as the Big Five. The Big Five broadly defines individuals' personality dispositions along five main dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN).

The personality model has gained popularity as an empirical tool in applied research for several reasons. Firstly, the personality traits have been shown to be stable in adulthood and - as such - unlikely to be seriously affected by life events (John & Srivastava, 1999; McCrae & Costa, 1994). Significant changes over one's lifetime are witnessed during childhood (Roberts *et al*., 2008; Roberts & Davis, 2016) and much of these changes are driven by biological factors rather than life situations (Soto & Tackett, 2015). Secondly, the model has proven to be a robust measure of personality traits across cultures (Barrick & Mount, 1991; Judge *et al*., 2002). Many studies have documented similar patterns in distribution of the traits by age and gender across different cultures (De Bolle *et al*., 2015; McCrae et al., 2010; Schmitt *et al*., 2007). Despite having an influence on performance in cognitive tests, the Big Five are documented to be uncorrelated with cognitive skills (defined as the ability to solve abstract problems) (Almulund *et al*., 2011). The Big Five, thus, constitutes clearly distinct factors in the analysis of labour market outcomes and - in addition and because of their stability - are less prone to the endogeneity problem that affects other measures of non-cognitive skills (Cubel *et al*., 2016).

Extraversion describes the extent to which individuals are assertive, ambitious, dominant, energetic, and looking for leadership roles. Extraverted individuals easily develop networks, which arises from their sociable nature. Neuroticism is associated with being moody, pessimistic, worrying a lot and getting offended easily; it is essentially a negative specification. Openness to Experience describes an individual's ability to seek new challenges and explore novel ideas. Individuals who score high in Openness to Experience are innovative, creative, and have an eagerness to explore new ideas. Apart from the intellectual curiosity aspect of this trait, these individuals desire autonomy and sometimes none conformity. Conscientiousness defines an individual's tendency to work hard, be efficient, and dutiful. These individuals strive for achievement, are organised and motivated. Conscientiousness individuals have an inclination towards rule following and exhibit planned - instead of spontaneous - behaviour (Hilger *et al*., 2015). Agreeableness individuals are forgiving, cooperative, trusting and altruistic in nature. Low values exhibit a tendency to be self-centred (Caliendo *et al*., 2014).

3.3 EVIDENCE ON PERSONALITY AND LABOUR MARKET OUTCOMES

This section aims at tracing development in the literature on personality traits and labour market outcomes. We focus on how the Big Five personality model explains labour market sectoral selection, earnings, and workers mobility.

3.3.1 Personality traits and sectoral choice

A long tradition of work in organisational psychology investigates the relationship between individual personality and occupation choice (Nieß, 2014). The theory of vocational choice (Holland, 1959) argues that individuals select into work environments that suit their personalities. The process of choosing an occupation thus results in congruencies between one's personality and their job. In a

review, Furnham (2001) provides evidence showing that individuals' job satisfaction closely relates to conformance between job and personality. Related to this theory, the person-environment fit theory (Caplan, 1987; Sims, 1983) explains how individuals make choices regarding occupations. They argue that individuals self-select into occupations perceived to fulfil their needs, which results in a match between occupation characteristics and one's personality attributes. Substantial empirical support from experimental research supports this theory (Cable & Judge, 1996). Schneider's (1987) attraction-selection-attrition model argues that there is a tendency amongst organisations to attract, select, and retain workers with more similar personality attributes. Closely related to the attraction component are propositions of both the theory of vocational choice (Holland, 1959) and the person-environment fit theory (Caplan, 1987; Sims, 1983). The theories, in sum, point to the fact that individual personality traits are important in framing occupational choices in the labour market.

Growing literature in labour economics examines the relationship between personality traits and labour market participation, focusing on employability (Derya & Pohlmeier, 2011; Fletcher, 2014; Heckman, 2006; Wichert & Pohlmeier, 2010), occupational choice (Cobb-Clark & Tan, 2011), sectoral choice (Villa & Sahn, 2015), as well as decision to enter or exit self-employment (Caliendo *et al*., 2014). Derya & Pohlmeier (2011), in German found that individuals who score high in conscientious and Openness are (on average) more likely to get a job placement faster. On the contrary, those high in Neuroticism scores face constrained job opportunities. Using a female sample of workers, Wichert & Pohlmeier (2010) found that all the Big Five traits - with the exception of Agreeableness - explain labour market participation. Extraversion and Conscientiousness increases participation probability, whereas Neuroticism and Openness decreases it. Fletcher (2013) found related results for the Netherlands: Neuroticism predicts unemployment, while Conscientiousness and Extraversion predict employment. In addition, the study showed that Extraversion has a particularly stronger effect on female employment than on male.

Cobb-Clark & Tan (2011) examined the link between personality and occupation sorting. The study found that agreeable males are less likely to select into leadership positions, which are more likely to be held by highly conscientious and Openness to Experience individuals. Villa & Sahn (2015) investigated the effect of personality traits on employees' sectoral choice in Madagascar. Using a multinomial logit approach, the study found that - in addition to traditional economic variables - personality variables explain one's sector of employment. For male workers, Conscientiousness and Openness to experience increased individuals' likelihood of formal employment, while Extraversion increased the likelihood of informal sector employment. On the other hand, Neuroticism increased the likelihood of male unemployment.

The empirical findings suggest that personality traits explain individuals' labour market occupational choices. However, their role in explaining sectoral selection within a developing country - whose economy is characterised by economic uncertainty - remains an important empirical question meriting further examination. Despite an awareness that employment in the two sectors generate

differences in economic outcomes, these concerns are yet to translate into a rigorous analysis of the Zimbabwean labour markets. We attempt to answer this question using Zimbabwean data.

3.3.2 Personality traits and earnings

A number of studies use the Big Five model to investigate the effect of personality traits on individuals' labour market earnings. These studies typically control for traditional earnings variables in the fashion of the Mincer specification, and augment it with the personality traits variables. Sahn & Villa (2015) for Madagascar, Nyhus & Pons (2005) and Fletcher (2013) for the Netherlands, Lee & Ohtake (2014) for Japan and the US and Lindqvist & Westman (2011) for Sweden, are some of the studies reporting that personality traits matter in explaining earnings. Personality traits have a direct effect on an individual's earnings through productivity (Fletcher, 2014; Judge *et al.*, 1999). A positive relation between Conscientiousness and earnings is reported, among recent studies (Fletcher, 2014; Lee & Ohtake, 2014; Villa & Sahn, 2015). The result is consistent across gender: for instance, Mueller & Plug (2006) reported a wage premium for women who are Conscientiousness. In respect of Openness to experience, some studies report a positive relationship between Openness and earnings (Heineck, 2011; Mueller & Plug, 2006). Heineck (2011) reported a 3% and 4% wage premium for a one-standard deviation increase in Openness for British female and male workers, respectively.

Agreeableness - an inter-personal trait (defining how one relates to others) - is widely reported to be negatively related to earnings (Fletcher, 2014; Heineck, 2011; Lee & Ohtake, 2014a; Mueller & Plug, 2006). Judge *et al*. (1999) argued that individuals who score high in Agreeableness tend to be passive in situations of conflict and have low bargaining power in wage negotiations. Furthermore, they tend to select into low paying occupations (Wichert & Pohlmeier, 2010). Another trait consistently shown to be associated with a wage penalty is Neuroticism (Cobb-clark & Tan, 2011; Gensowski, 2018; Heineck & Anger, 2010; Mueller & Plug, 2006; Nikolaou, 2012; Nyhus & Pons, 2005). Neuroticism negatively associates with job performance and - given the negative association between low productivity and pay - individuals who score high in this trait on average earn less in the labour markets. In respect of Extraversion, evidence of its effect on earnings is mixed. Fletcher (2014) found a positive relation between Extraversion and earnings. However, a large selection of studies reports that Extraversion has no effect on earnings (Nyhus & Pons, 2005; Villa & Sahn, 2015; and Lee & Ohtake (2014).

Few studies consider both the formal and informal sector in analysing the effects of personality traits on earnings, yet it is plausible to think of sector specific returns to personality traits. An exception is Villa & Sahn (2015), who estimated sectoral returns to personality traits in Madagascar. The study found a wage premium for highly conscientious females in formal sector jobs and males in informal sector jobs. Neuroticism negatively relates to female formal sector earning and male informal sector earnings. Openness to Experience negatively explains female formal sector earnings. The findings

suggested that specific skills may be valued more for a given gender by sector of employment. We extent this research to a cohort of Zimbabwean workers in this study.

Personality traits can affect earnings indirectly through education attainment (Almulund *et al.*, 2011; Borghans *et al.*, 2008; Gensowski, 2018; Heckman *et al*., 2006). Substantial literature documents the importance of traits on educational achievement for representative samples of American and selected European countries (see reviews by Almulund *et al*., 2011; Borghans *et al*., 2011; Brunello & Schlotter, 2011). Conscientiousness and Openness are consistently reported to positively influence educational achievements; the other traits (Agreeableness, Neuroticism and Extraversion) negatively associate with educational outcomes (Gensowski, 2018). The socialising component of Extraversion - for instance - may take away student's time from studies (Connell & Sheikh, 2011).

Apart from the educational channel, personality traits can also indirectly explain earnings through occupational choice (Cobb-Clark & Tan, 2011; Lindqvist & Westman, 2011; Nikolaou, 2012). Unskilled employees and managerial level employees have a higher return to non-cognitive skills, while skilled workers have a higher return to cognitive skills (Lindqvist & Westman, 2011). Extraversion and Conscientiousness are rewarded the higher one climbs the occupational ladder (Gensowski, 2018). Related results are reported in a recent study done in two countries: Extraversion explains earning for the lower and high-income earner brackets in Japan, while Agreeableness and Conscientiousness are rewarded for male low to medium income earners in the United States (Lee & Ohtake, 2014). In a review, Agreeableness and Neuroticism predicted job performance positively and negatively respectively - where individuals work in groups - while Openness to experience explained success in artistic jobs (Brunello & Schlotter, 2011).

In addition to occupational choice, another potential channel is through choice of hiring channel; agreeable individuals are more likely, for instance, to find employment through networks (Cobb-Clark & Tan, 2011). Extraversion has a wage premium for formal hires compared to network hires (Hilger *et al*., 2015). Ignoring these may understate the effect of traits on earnings. There is, however, a constraint in carrying out studies of this nature: they require longitudinal data sets with traits gathered pre-labour market entry. Our data limits us from looking at the occupational sorting angle; rather, we add to the literature by considering the informal sector.

Personality traits have also been studied in respect of the gender wage gap (Bowles *et al*., 2001; Cobb-Clark & Schurer, 2012; Gensowski, 2018; Nyhus & Pons, 2012). Interestingly, there is evidence showing that personality traits indirectly explain the gender wage gap through occupation (Cobb-Clark & Tan, 2011; Nikolaou, 2012). A UK study found that ignoring the indirect channel underestimates the personality effects on the gender wage gap (Nikolaou, 2012). For instance, at the age of 30, a good personality trait - occupation match - has productivity benefits that help women narrow the gender wage gap.

3.3.3 Personality traits and employee mobility

Employee mobility, often defined and studied in the context of turnover (external mobility or job changes), remains an important empirical question in the field of labour economics. Job mobility may result in loss of firm and occupation-specific human capital (Kambourov & Manovskii, 2008, 2009), which is a lost investment for training firms. Employees search for better jobs as a way of career progression; if their skills match a new occupation, they get rewarded (Fitzenberger *et al*., 2015). In the same vein, non-training firms may search for trained employees and offer them attractive packages (job poaching) (Wolter & Ryan, 2011). Despite the theoretical benefits of this subject matter, understanding how personality traits affect individual decisions to quit is important, as it allows for cost savings associated with turnover (Zimmerman, 2008). Employers may take into account someone's personality disposition in screening job applicants. In addition, firms may focus on retaining individuals with personality attributes considered valuable to the enterprise, and let go of those with traits considered toxic to a harmonious working environment (whenever the need for laying off arises).

Closely related to individuals' mobility is job satisfaction, defined as one's "effective attachment to their job" (Tett & Meyer, 1993). In a meta-analysis, Judge *et al*., (2002) show that three of the Big Five factors - Neuroticism, Extraversion, and Conscientiousness - consistently show moderate correlations with job satisfaction. Workers who are passionate about their jobs have a lower likelihood of leaving their workplace and the converse is true for those with a negative attitude towards their work. This is an indirect channel through which personality influences turnover (Van Vianen *et al*., 2003; Zimmerman, 2008). Highly neurotic individuals tend to encode and remember negative information and are more likely to have a negative perception of themselves and their environment. They tend to feel more insecure, which may force them to leave their current jobs (Maertz & Boyar, 2012; Maertz & Griffeth, 2004). The stress associated with new duties may particularly force neurotic individuals with less tenure to quit.

Highly conscientious individuals on the contrary, are more likely to value contractual obligations. In addition, they tend to feel indebted for fair treatment and perceived support from the firm (Eisenberger *et al*., 2001). They will stick with the firm until a point the supposed 'debt' is paid. Employees who score high in Agreeableness and Extraversion are more likely to create relationships with other workers, which may motivate them to stay. This is likely to increase job satisfaction, which may indirectly reduce job turnover (Zimmerman, 2008). It is, however, possible that highly extraverted employees will exploit networks outside of the firm to keep in touch with emerging opportunities elsewhere. What is less understood, and often not taken into account, is how individual personality traits interact with the environmental circumstances in determining mobility decisions. Employment shocks within the firm may influence one's decision to stay or to move. However, the way one interprets an employment shock, and reacts to it, may differ depending on their personality

orientation. In this study, we seek to establish the possible ways through which individuals' personality traits may explain external job mobility.

Summary

Emerging literature documents personality traits as vital in explaining labour market outcomes. Much focus has been on developed countries (Europe and US), and only few studies extend this research to developing countries[11]. We add to the literature by focusing on the Zimbabwean labour market. Unlike most studies that focus on earnings, we extend the research to include sectoral selection and individual mobility patterns. Our study belongs to the literature that empirically tests the relationship between personality traits and individual labour market outcomes, post labour market entry.

3. 4 DATA AND METHODS

The Southern African Labour and Development Research Institute (SALDRU) enumerated the Matched Employer–Employee Panel Data for Labour Market Analysis in Zimbabwe (MEPLMAZ) in 2015 and 2016. The primary purpose was to investigate manufacturing sector labour dynamics in an environment characterised by economic uncertainty. Trained enumerators administered an electronic version of the worker questionnaire to participants at their workplace. Wave 1 surveyed 1 692 workers (1 385 formal and 175 informal workers) from 327 firms (195 formal and 132 informal sector firms). Informal sector firm owners (self-employed) were also administered a module of the worker questionnaire, and we grouped them together with the informal sector employees. Respondents were drawn from four main industrial cities in Zimbabwe: Harare (59.3%), Bulawayo (32.7%), Gweru (3.5%), and Mutare (4.5%).

3.4.1 First wave of the MEPLMAZ data

The 2015 wave of the MEPLMAZ offers a uniquely detailed account of worker information, including a 15-item inventory of the Big Five personality traits questionnaire. Confirmatory factor analysis is performed on the reduced item instrument scores (15-item), and five factors are extracted. We label the factors Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN)[12]. Reduced item instruments have facilitated the inclusion of personality modules in national surveys[13] that collect labour market data. This data offers us a unique opportunity to examine the empirical relationship between traits measured using a reduced item instrument and labour market outcomes within a developing country context.

Appendix B, Table B.1 provides the basic summary statistics focusing on the main variable of interest, disaggregated by employment sector. On average, formal sector workers earn more (US$378.92), as compared to their informal sector employment peers (US$288.70). In addition,

[11] For example Glewwe, Huang and Park (2017) in China and Villa and Sahn (2015) in Madagascar
[12] The extraction procedure, validity and reliability tests is provided in Chapter 1.
[13] Studies have recently used reduced item instruments to investigate the effects of personality traits on LMO (Heineck & Anger, 2010; Nyhus & Pons, 2012)

amongst the informal sector participants, the self-employed (owners of informal firms) earn more (US$362.98), as compared to the wage earners in this sector (US$229.15). The sample mean age is 40.1 years; formal sector workers (41.6 years) are relatively older compared to informal sector workers (33.4 years). Amongst the informal sector participants, the self-employed (mean of 37 years) are relatively older, as compared to informal sector employees (mean of 30 years). Young workers may find it difficult to get jobs in contracting formal manufacturing; hence, they opt for informal jobs.

The sample average tenure of 11.5 years is driven by the formal sector employees (12.7 years), which is significantly different from the informal sector average of 5.8 years (t = 15.215, p-value < 0.00). Formal sector employees report longer previous job experience (5.5 years) compared to informal sector workers (4.4 years). The true mean differences between these two samples is statistically different from zero (t = 3.3064, df = 553.15, p-value = 0.001). It is worth noting that average current job tenure is greater than experience gained from previous jobs. The average education attained for the sample is 11.3 years; this is comparable between informal (11.1) and the formal sector (11.5) workers. In terms of potential experience[14] (mean = 22.7 years), formal sector employees report longer potential experience (24.2 years) compared to informal sector workers (16.3 years).

A significant proportion of the sample (80.9%) is married; the ratio is higher in the formal sector (83%) as compared to the informal sector (70.7%). Pearson's Chi-squared test results indicate a significant association between marital status and employment sector (Chi-squared = 23.476, p-value <0.000). The average household size is 4.45; informal sector participants, however, have slightly smaller households (4.1) compared to their formal sector peers (4.54).

3.4.2 Second wave of the survey

In 2016, MEPLMAZ participants were re-interviewed. Wave 2 of the survey captured detailed information of changes in workers' employment situations between the two waves. It traced individuals' transition within and between jobs, which allows us to investigate manufacturing sector employment dynamics. In particular - and related to our third objective - we take note of employee turnover between the two waves. From the initial wave, 402 individuals dropped out of the survey, and of the 1 240 that were interviewed, 1043 (84.4%) indicated that there were still employed by their previous firms and 197 (15.6%) had left their previous jobs.

For the purposes of this study, our interest is in identifying who moves and who stays within firms that record turnover. We identify and restrict our analysis to workers working in firms that recorded job mobility. This reduces the firm and worker samples to 98 and 663 respectively. Table 3.1 summarises the job transition matrices by a vector of firm and individual characteristics. The subsample is predominantly formally employed (97.7%); almost 30% of participants left jobs. Despite

[14] Potential experience is the difference between age and years of education less six years.

accounting for only 19.2% of the sample, a relatively larger proportion of movers by gender were females (35%) compared to males (28%). The mean difference in age between movers and stayers is negligible (40.5 and 42 years); a two-sample t-test (p-value = 0.13) confirms equality of means. However, disaggregating movers by age groups shows that a relatively large proportion of movers is amongst those at the lower (35%) and upper (32%) end of the age distribution, compared to middle age (24%). Pearson's chi-square test confirms a significant association between these age categories and mobility (Chi-square = 8.36, p-value = 0.039).

Table 3.1: Proportion of movers by selected variables

Variable	Description	Stay	Left	*p*-value	Vol	Invol	*p*-value	Total
Firm size	micro	50%	50%	0.033	67%	33%	0.1095	12 (1.8%)
	small	61%	39%		36%	64%		99 (14.9%)
	medium	74%	26%		41%	59%		254 (38.3%)
	large	71%	29%		27%	73%		298 (44.9%)
Emp/shock	shock	69%	31%	0.193	31%	69%	0.186	252 (46.8%)
	no shock	74%	26%		42%	58%		286 (53.2%)
Gender	female	65%	35%	0.198	34%	66%	0.88	127 (19.2%)
	male	72%	28%		35%	65%		546 (80.8%)
Firm location	Harare	70%	30%	0.197	34%	66%	0.124	439 (61.5%)
	Bulawayo	71%	29%		42%	58%		203 (30.6%)
	Gweru	58%	42%		8%	92%		31 (4.7%)
	Mutare	86%	14%		33%	67%		21 (3.2%)
Age group	less 35	65%	35%	0.039	49%	51%	0.003	221 (33.3%)
	35 to 50	76%	24%		26%	74%		290 (43.7%)
	over 50	68%	32%		25%	0.75%		151 (22.8%)
Total		**467 (70%)**	**196 (30%)**		**128 (65%)**	**68 (35%)**		**663**

Note: Employment shock is a dummy variable that defines firms that laid off workers within the period of three years prior to the initial survey (2013-2015). The other columns split movers between voluntary or involuntary mobility and the last column sums up the totals per variable.

Source: Author, 2019.

A disaggregation of movers by firm size shows that a relatively higher proportion of movers were in small firms (39%) followed by large firms (29%) and medium-sized firms (26%). This is even higher for micro-sized firms (50%); however, they only constitute 1.3% of the sample. There is a relatively high proportion of movers amongst workers in firms that experienced an employment shock between 2013 and 2015 (31%) compared to firms that did not (26%). Pearson's Chi-squared test, however, suggests an insignificant association between shocks and mobility (p-value > 0.1). Of the 196 workers who left jobs, a majority became unemployed (54.4%), 23.3% were informally employed, while only 18.3% found formal jobs. There are limited reemployment options after leaving one's job, a plausible explanation for workers holding onto bad job matches (low remuneration and bad working conditions).

3.4.3 Reasons for Mobility

Identifying who moves is an important first step, though it is equally crucial to understand how movers differ from stayers. For instance, firms may want to keep workers they consider valuable and sacrifice those perceived to be easily replaceable. On the other hand, as highlighted in the literature section, certain personality traits are associated with intentions to quit; for example, highly neurotic individuals may experience job dissatisfaction and may initiate the process of moving. Individuals in struggling firms may move as a way to cushion themselves from imminent employment shocks. We infer from the data by examining the reasons cited for job mobility in Figure 3.1:

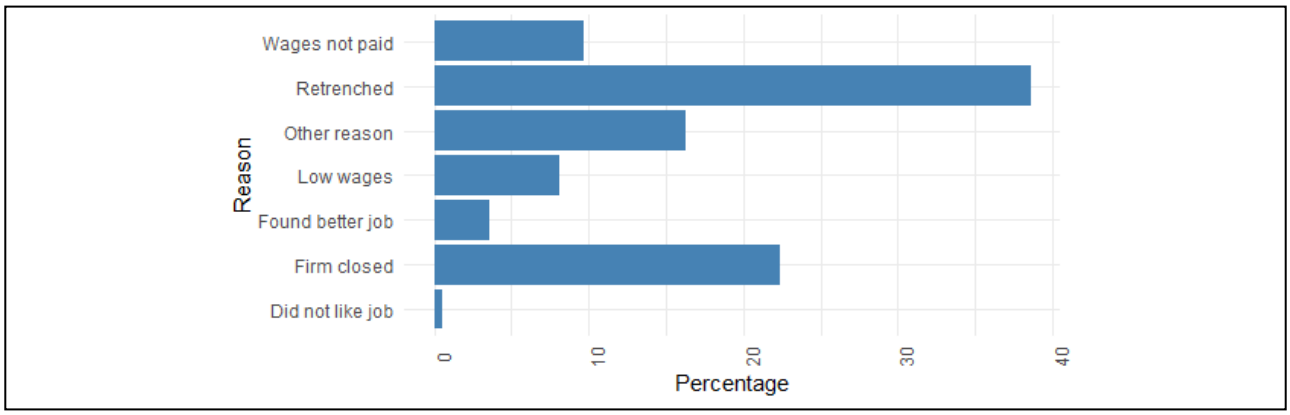


Figure 3.1: Reason for leaving previous employment

Source: Author, 2019.

Retrenchments (38.6%) and company closures (22.3%) were the leading causes of job mobility (Figure 3.1). Untenable employment conditions were a contributory factor; non-payment of wages (9.6%) and low wages (8.1%) were cited. Some found better jobs (3.6%), while 1.5% resented their jobs, with the other percentage (16.2%) citing other reasons. Following Fuller (2008), we aggregate the reasons for mobility under two broad categories: voluntary and involuntary mobility. Figure 3.2 gives a detailed summary of movers, distinguishing them by motives of mobility. The green line indicates employees who stayed, the grey line those that moved, while the red and black lines highlight involuntary and voluntary movers respectively. The data indicates that a majority of the employees cite involuntary reasons (65.3%) for mobility, suggesting that given options these employees would have wanted to stay in their firms.

Table 3.2 summarises different subsamples that can be constructed from the mobility sample (Subsample A). Subsample B focuses on individuals who left their jobs, distinguishing between workers that voluntarily left (34.7%) and those who left involuntarily (65.3%). We match voluntary and involuntary movers - within firms - with corresponding stayers. Subsample C identifies involuntarily movers (71.2%) and those who stay (27.8%) within the same firms. Subsample D focuses within firm voluntary movers (29.6%) and stayed (70.4%).

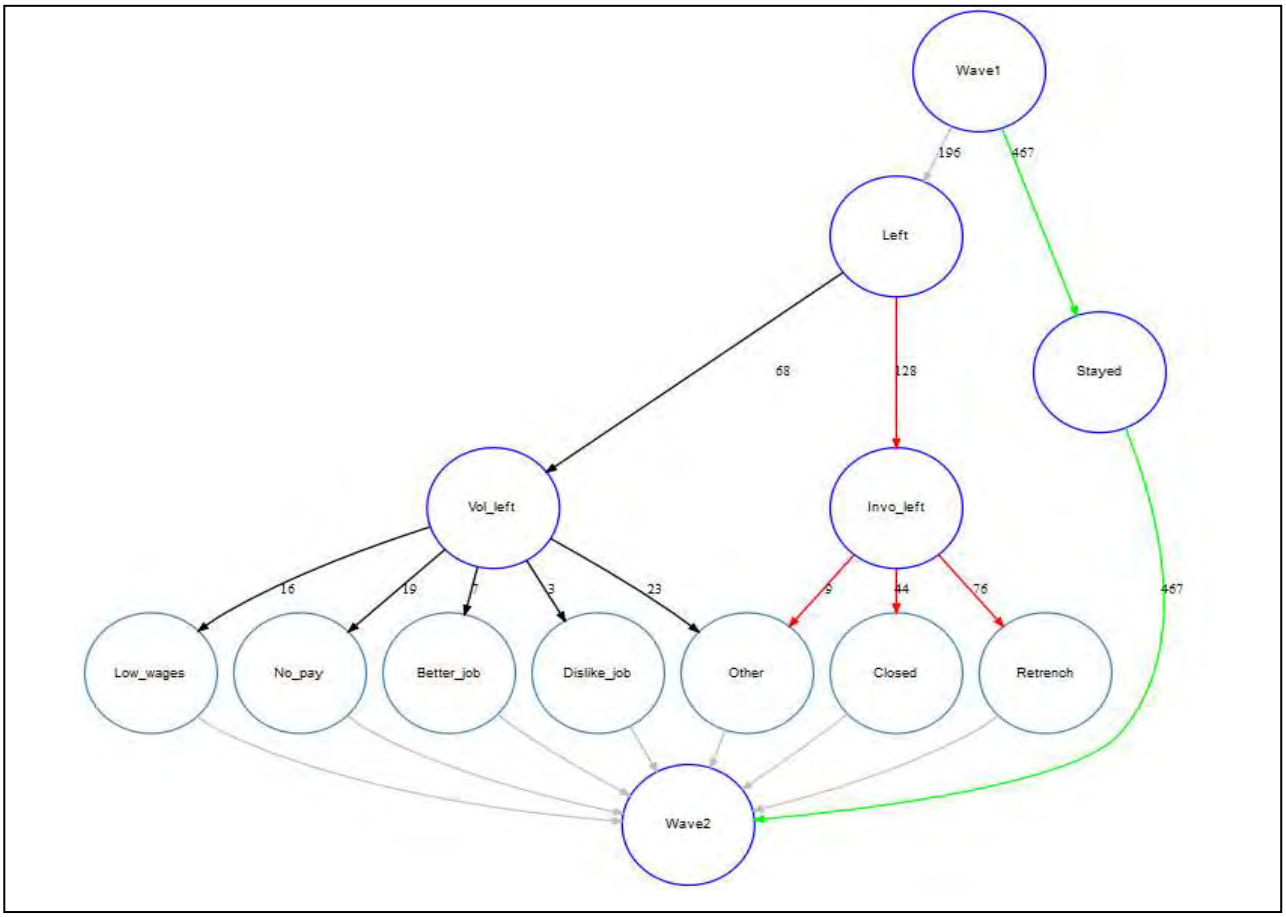


Figure 3.2: Transition of workers between Wave 1 and Wave 2

Source: Author, 2019.

Table 3.2: Employee mobility samples

Subsample		**Stay**	**Left**	**Total**
All workers		1043	197	1240
Subsample A		467 (70.4%)	196 (29.6%)	663
Subsample B	Voluntary	-	68 (34.7%)	
	Involuntary	-	128 (65.3%)	
Subsample C (Involuntary vs stay)		333 (72.2%)	128 (27.8%)	491
Subsample D (Voluntary vs stay)		280 (70.4%)	68 (29.6%)	397
	Stayed	467 (70.4%)		
Subsample E	Voluntary		68 (10.3%)	
	Retrenched		84 (12.7%)	
	Firm closed		44 (6.6%)	
Totals		**467 (70.4%)**	**196 (29.6%)**	

Source: Author, 2019.

Subsample E returns the mobility sample but splits movers by motives of mobility; in particular, amongst those who involuntarily, we distinguish retrenchments from those that left due to company closures. We argue that a broad classification of movers and stayers may potentially hide important information that explains workers' mobility patterns. For instance, retrenchments and firm closures are both involuntary; however, they are clearly distinct in the strict sense. Hence, it may be wrong to

lump them as one. This subsample allows an examination of the effect of individuals' personality traits on nature of mobility using a multinomial framework.

3.4.4 Selection into occupational sector

The role of human capital variables and personality traits in determining sectoral selection is important; in particular, they indirectly influence individual success in the labour markets. The study models sectoral occupational as a multinomial process following McFadden (1973). Our model of selection into sectoral occupations has three categories: formal sector employment, informal employment, and self-employment. The distinction between informal employment and self-employment is that the latter owns the informal firms that employ the former. We specify the multinomial logistic model as follows:

$$Occ_{it} = \delta_0 + \delta_1 P_{it} + \delta_2' X_{it} + \mu_{it} \quad \text{.....(3.1)}$$

In estimating occupational selection, we consider factors thought to influence individuals labour supply decisions; that is, variables that predict earnings (Rankin *et al.*, 2010; Villa & Sahn, 2015). We focus on variables that predict earnings once one gets the job and those that influence the reservation wage. Our dependent variable - Occ_{it} is the observed occupational category for individual i at time t - P_{it} is a vector of the Big Five personality variables and X_{it} is a set of demographic characteristics including educational level (self and parents), marital status, and household size. The model is estimated after workers have selected into employment using data from the first wave of the survey (2015).

3.4.5 Determinants of Earnings

Labour market earnings constitute a major source of income for a majority of developing countries citizens. An important empirical question worth interrogating is how heterogeneity in personality traits may explain observed differences in earnings, over and above the traditional economic variables. The study estimates the traditional Mincer equation and control for personality traits. Following Nyhus & Pons (2005) and Nikolaou (2012), the basic formulation of the Mincer equation augmenting for personality traits is given by:

$$W_{ij} = \alpha_0 + \alpha_1 P_{ij} + \alpha_2' X_{ij} + \varepsilon_{ij} \text{.....(3.2)}$$

The dependent variable (W_{it}) is the logarithm of monthly wage and P_{it} is a vector of the Big Five personality variables (Openness, Conscientiousness, Extraversion, Neuroticism, and Agreeableness). The traditional economic variables including demographic characteristics, years of education, experience, tenure, job characteristics, firm size, industrial sector, and location are captured by X_{it}, while ε_{it} is the error term. All variables were measured after workers had already entered the labour market in 2015. We also control for endogenous selection in our earnings equation through the Durbin & McFaden (1984) methodology, following other studies in this literature (Rankin *et al.*, 2010; Villa & Sahn, 2015).

3.4.6 Employee mobility

We exploit information drawn from the second wave of the survey, where almost 30% of respondents reported job mobility. The study models the relationship between personality traits and employee mobility using discrete choice models, in particular probit models. Essentially, we test the hypothesis that personality traits explain job mobility in Zimbabwe's manufacturing sector. The estimation model is specified as follows:

$$Pr(left\_firm_{it} = 1|P, X) = \Phi\ (\sigma_j' P_i + \sigma_j' X_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.3)}$$

Our dependent variable $(left\_firm_{it})$ is bivariate, and we code participants one (1) if they left a firm and zero (0) if they stayed. The Big Five personality variables are captured by P_{it}, and X_{it} is a set of explanatory variables including age, marital status, years of education, household size, tenure, firm level employment shocks, and sector of employment that explains job mobility.

To estimate worker's nature of mobility, we employ a multinomial model approach specified in equation 3.4. The predicted probability that an individual i leaves their job due to nature of mobility j is given by

$$Pr\big(left\_N_{ij} = 1\big|P, X\big) = \frac{exp\ (\delta_j^I P_i + \theta_j' X_i)}{\sum_{k=1}^{3} exp\ (\delta_k^I P_i + \theta_k' X_i)}\ , j = 1,2,3 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(3.4)}$$

Where $j = 1$ for voluntary mobility, 2 for involuntary mobility and 3 for closed firm. Our primary interest is in establishing the sign and significance of the coefficient on personality traits variables(δ_j^I). We also include a vector X_{it} that contains controls for demographic and human capital variables that explain mobility.

3.5 ESTIMATION RESULTS

In this section, we summarise and discuss the main research findings focusing on the three main labour market outcomes: sectoral occupation, earnings, and job mobility.

3.5.1 Labour Market Selection

i) Individuals' characteristics and occupational selection:

Following Dubin and McFadden (1984), we adopt a multinomial logistic model to predict the probabilities that a worker selects into each of these three categories. Table B.2 reports the estimated multinomial logit model parameters for selection into labour market sectors. Formal employment is the base outcome, and we interpret the results as the likelihood of being in an alternative sector (informal employment or self-employment) relative to formal employment.

For easy of interpretations, Table 3.3 summarises the multinomial logistic model average marginal effects:

Table 3.3: Average marginal effects on the probability of employment in a given labour market

	(a)		(b)		(c)	
	informal	self emp	Informal	self emp	informal	self emp
age	-0.017***	0.020***	-0.018***	0.021***	-0.017***	0.020***
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)
agesqr	0.121***	-0.274***	0.134**	-0.282***	0.120**	-0.270***
	(0.056)	(0.075)	(0.055)	(0.079)	(0.055)	(0.075)
male	-0.01	0.003	0.007	0.0163	0.013	0.021
	(0.018)	(0.021)	(0.018)	(0.018)	(0.018)	(0.018)
married	-0.021	0.003	-0.019	0.002	-0.025	0.002
	(0.017)	(0.021)	(0.017)	(0.021)	(0.017)	(0.021)
hhsize	-0.012**	0.002	-0.011***	0.002	-0.012***	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
yrs_educ	0.03	-0.013	0.027	-0.012	0.027	-0.014
	(0.021)	(0.014)	(0.021)	(0.015)	(0.021)	(0.015)
educsqr	-0.003**	0.000	-0.002**	0.000	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Ndebele	0.032	-0.044**	-0.025	-0.048**	0.002	-0.026**
	(0.028)	(0.019)	(0.027)	(0.019)	(0.019)	(0.019)
Manyika	-0.027	-0.021	0.028	0.023	0.025	0.019
	(0.018)	(0.021)	(0.018)	(0.022)	(0.018)	(0.022)
Karanga	-0.005	-0.025	-0.004	-0.024	0.002	-0.026
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Foreigner	0.058	-0.089***	0.07	-0.090***	0.069	-0.089***
	(0.118)	(0.012)	(0.119)	(0.012)	(0.121)	(0.012)
Openness			0.157***	0.165***		
			(0.027)	(0.029)		
Conscientious			-0.200***	-0.284***		
			(0.057)	(0.060)		
Extraversion			-0.494***	-0.674***	-0.055***	-0.020
			(0.140)	(0.145)	(0.020)	(0.021
Agreeableness			0.444***	0.662***		
			(0.144)	(0.148)		
Neuroticism			0.287***	0.396***	0.039***	0.019
			(0.083)	(0.085)	(0.014)	(0.014)
Harare	0.163***	0.214***	0.151***	0.201***	0.166***	0.208***
	(0.038)	(0.697)	(0.381)	(0.674)	(0.039)	(0.070)
Bulawayo	0.097***	0.233***	0.081**	0.213***	0.101**	0.228***
	(0.042)	(0.714)	(0.041)	(0.069)	(0.042)	(0.071)
Cluster1					0.024**	0.013
					(0.009)	(0.010)
No. Obs.	**1,655**	**1,655**	**1,655**	**1,655**	**1,655**	**1,655**

Note: We compute the multinomial marginal effects using the margins command in Stata 14.

Source: Author, 2019.

We estimate three different specifications of the occupational selection model, the basic model (a) and two other specifications (b) and (c) that control for personality traits. For now, we focus on the basic model. We report a convex relationship between age and informal sector employment, and a concave relationship between age and self-employment. Increasing age decreases the likelihood of informal employment relative to formal employment, but increases probability of self-employment

relative to formal employment (Table 3.3, column 1). In an environment of shrinking formal manufacturing activities, entry into formal employment is particularly difficult for new entrants. Young workers face the option of queuing for formal employment (staying unemployed) or entering the relatively free informal sector, an option they often take (as supported by our data). A unit increase in household size is associated with a 1% less probability of informal employment, relative to formal sector employment; the relationship is positive but statistically insignificant in respect of self-employment. A year increase in education decreases the probability of informal sector employment relative to formal sector employment by 2.4%; the relationship is positive but statistically insignificant in respect of self-employment. Low education attainment constrains formal sector employment opportunities, in particular a lack of specific skills required in the formal sector that may potentially be a barrier to formal sector entry.

We add controls for parental education, primary and secondary school distance, as well as one's ethnic background: the results largely remain unchanged (not presented in Table 3.2). However, after adding education squared, only the square is significant but only for informal employment. We control for individuals' ethnic background, and take Zezuru as the reference category. Individuals born in the Matebeleland region (Ndebele) are less likely to select into self-employment than formal employment (compared to the Zezurus). Specifically, we report a 4.4% lower probability of self-employment relative to formal employment for individuals born in Matebeleland. There are no significant differences in choice of occupation between the Shona Zezuru and Shona Manyika, suggesting no intra-ethnic differences in occupational choices. Workers of foreign origins have an 8.9% less probability of self-employment than formal sector employment, compared to Shona Zezurus. These results are robust to the inclusion of location variables. In respect of location, dummies for Bulawayo and Harare show a higher likelihood of both informal employment and self-employment. This may be a sample artefact, as informal sector participants were sampled from Harare and Bulawayo.

Controls for parental education (both mother and father), as well as remittances are insignificant (results not included in the Table 3.2). Increasing primary school distance by a kilometre increases the probability of informal employment by almost 2%, relative to formal employment. Demographic variables, gender, and marital status are statistically insignificant, and the result is consistent across different specifications of the sectoral selection model.

ii) Personality traits and occupational selection:

Table 3.3 column (b) controls for the Big Five personality factors in the sectoral selection model ,following Villa & Sahn (2015). Our results show a significant association between personality traits and a worker's occupational sector. Interestingly, personality traits relate to sectoral occupation in an almost similar fashion for both categories of informal employment. Openness to Experience, Agreeableness and Neuroticism are associated with a high likelihood of self-employment and

informal sector employment, relative to formal sector employment. On the other hand, Conscientiousness and Extraversion explain a lower likelihood of both forms of informal sector activities, relative to formal sector employment.

Interestingly, we infer that the predicated probabilities differ depending on worker's location on the Big Five personality trait distribution. Table 3.4 presents the predicted probability of selection into a given occupational sector relative to formal employment. We calculate the probabilities at the 25th and 75th percentile of each of the Big Five personality traits. A closer look at the results indicates differences in predicted probabilities of selection into a given occupational category, between individuals who score high and low in each of the Big Five trait attributes.

Table 3.4: Predicted probabilities of sectoral selection

	Informal employment		**Self-employment**	
	25th quantile	75th quantile	25th quantile	75th quantile
Openness	-0.064***	0.086***	-0.067***	0.090***
Conscientiousness	0.051***	-0.093***	0.072***	-0.132***
Extraversion	0.220***	-0.238***	0.306***	-0.324***
Agreeableness	-0.180***	0.250***	-0.268***	0.372***
Neuroticism	-0.178***	0.113***	-0.245***	0.157***

Source: Author, 2019.

For instance, at the 25th percentile of Openness distribution, the predicted probability of informal employment relative to formal employment is 6.4% lower. At the 75th percentile, the predicted probability of informal employment relative to formal is almost 9%. There is a similar pattern in differences between the quantiles across all the five personality traits variables. Generally, higher Conscientiousness and Extraversion are associated with relatively higher probabilities of being in formal sector employment, whereas higher levels of Openness, Agreeableness, and Neuroticism are associated with lower probabilities of formal sector employment.

The results confirm theoretical predictions of the attraction-selection-attrition model (Schneider, 1987) which argues that there is a tendency amongst organisations to attract, select, and retain workers with more similar personality attributes. Similarly, the selection of individuals into informal sector employment may in part be explained by the theory of vocational choice. Holland (1959), argues that individuals select into work environments that suit their personalities. We further check whether gender differences in personality traits may help explain sectoral selection by including an interaction term between personality traits and gender. The interaction terms are insignificant, suggesting that gender differences in personality traits fail to explain occupation sorting.

iii) Personality and Occupation Selection: Cluster Analysis Results

The magnitude of the marginal effects of personality traits seem inflated, and we suspect this could arise from certain personality trait attributes moving together. We use cluster analysis – a class of

techniques that are used to classify objects or cases into relative groups called clusters, to examine for this. Specifically we rely on the 'ClustOfVar' package in R for our analysis (Chavent & Kuentz-simonet, 2012). Figure 3.3 is a cluster dendrogram (tree diagram) showing how closely each of the five personality trait variables are related. Our interest is in identifying and extracting the optimal number of clusters that explain our personality trait data. The stability function in R provides a convenient way of determining the number of clusters to return. We find that three clusters explain our trait data - Neuroticism and Extraversion form two clusters that have weak correlations with the other three factors. A worker who scores high in Conscientiousness also scores high in Openness to Experience and Agreeableness. We use principal component analysis to construct an index that represents the three factors that constitute the three-item cluster.

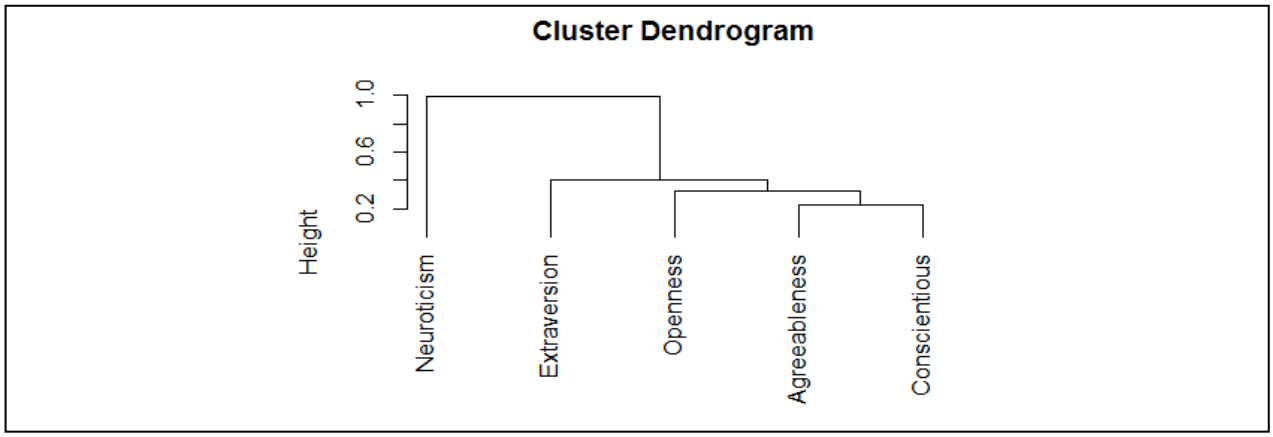


Figure 3.3: Cluster Dendrogram

Source: Author, 2019.

We replace the three correlated personality factors with the extracted principal component and estimate the occupation selection multinomial model in Table 3.3 (column 3). The personality trait variables consistently return the same signs as the model before. A one standard deviation increase in Extraversion is associated with a 5.6% less probability of informal employment, as compared to formal employment. On the other hand, one standard deviation increase in Neuroticism is associated with a 3.9% increase in the probability of informal employment. Individuals who score high in Agreeableness, Conscientiousness and Openness are more likely to participate in the informal sector labour market. A unit increase in the principal component representing this cluster of personality attributes is associated with 2.4% more probability of informal sector employment.

3.5.2 Labour Market Earnings

i) Basic Mincer Equation:

We begin in Table 3.5, column (1) by estimating the standard Mincer earnings equation with no controls for occupational selection and personality traits. We report a concave relationship between age and earnings, a finding common in the earnings literature (Falco *et al*., 2011). Earnings' increase with age, reaching a maximum at around 50 years, and start to decline. We interpret this as the

diminishing marginal returns to skills acquired through work experience. We report an earning penalty for females, an empirical result that confirms the existence of a gender wage gap. Similar results are reported for both developed and developing countries (Fletcher, 2014; Nikolaou, 2012; Nyhus & Pons, 2012). Married workers - on average - earn more compared to their single peers.

Table 3.5: Mincer Earnings Equation

Dependent variable: Log Monthly wage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	4.568***	4.609***	4.597***	4.566***	4.562***	4.563***	4.633***	4.620***
	(0.312)	(0.314)	(0.313)	(0.313)	(0.313)	(0.312)	(0.315)	(0.314)
Age	0.031***	0.030***	0.031***	0.031***	0.031***	0.031***	0.030***	0.031***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Agesqr	-0.393***	-0.380***	-0.388***	-0.394***	-0.395***	-0.393***	-0.385***	-0.391***
	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)
Male	0.227***	0.222***	0.225***	0.227***	0.228***	0.229***	0.227***	0.229***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Married	0.148***	0.149***	0.148***	0.148***	0.148***	0.148***	0.149***	0.147***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Experience	0.016**	0.016**	0.016**	0.016**	0.016**	0.016**	0.016**	0.015**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Expersq	0.003	0.002	0.003	0.003	0.003	0.003	0.003	0.004
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Tenure	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
yrs_educ	-0.074*	-0.076*	-0.077*	-0.074*	-0.074*	-0.074*	-0.080*	-0.080*
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Educsqr	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Training	0.178***	0.177***	0.177***	0.178***	0.179***	0.181***	0.181***	0.181***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.052)	(0.052)	(0.052)
Informal	-0.334***	-0.345***	-0.341***	-0.334***	-0.333***	-0.332***	-0.356***	-0.349***
	(0.062)	(0.063)	(0.063)	(0.062)	(0.063)	(0.062)	(0.064)	(0.063)
Openness		0.026					0.080	
		(0.023)					(0.069)	
Conscientious			0.029				-0.020	
			(0.028)				(0.148)	
Extraversion				-0.003			-0.216	-0.102**
				(0.022)			(0.365)	(0.049)
Agreeableness					-0.007		0.141	
					(0.023)		(0.368)	
Neuroticism						0.012	0.130	0.066**
						(0.021)	(0.215)	(0.033)
cluster1								0.046**
								(0.021)
R^2	0.199	0.200	0.200	0.199	0.199	0.200	0.203	0.202
Adj. R^2	0.193	0.193	0.193	0.193	0.193	0.193	0.194	0.195
Num. obs.	1453	1453	1453	1453	1453	1453	1453	1453
RMSE	0.620	0.620	0.620	0.620	0.620	0.620	0.620	0.620

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Author, 2019.

An additional year of tenure is significantly associated with a 0.7% increase in earnings. This may reflect the effect of employer learning on earnings, as a worker's true ability and productivity reveals itself over time (Gensowski, 2018; Light & McGee, 2015). Years of previous job experience positively correlate to earnings, indicating a wage premium to the human capital embedded in one's accumulated labour market experience. Against a backdrop of a massive brain drain witnessed as Zimbabwe's economic challenges persisted, firms may offer high wages to retain their skilled workers. On-the-job training (sponsored by the firm) positively correlates to earning. The result shows the importance of human capital investment while the worker is on the job (Konings & Vanormelingen, 2015). A worker's educational level, as approximated by years of formal education, is positively associated with monthly earnings. The returns to education increases at a decreasing rate with an additional year of education. Other studies done in developing countries confirm this result (Gensowski, 2018; Hilger *et al*., 2015; Villa & Sahn, 2015). Informal sector employment comes with a wage penalty in Zimbabwean manufacturing. Employment relations in this relatively open entry sector are largely unregulated and minimum wage legislation is not applicable.

The analysis so far fails to take into account the role of unobservables in explaining earnings. However, due to the likely presence of selections based on unobservables, ordinary least squares (OLS) estimates may be biased. To address this, we account for selection using the Durbin - McFadden (1984) procedure (Appendix B, Table B.6). We report significant associations between the Durbin & McFadden (1984) selection terms (DMF infor_emp) and manufacturing sector earnings equation. The result suggests that endogenous selection is important when estimating individuals' earnings.

ii) **Mincer Earnings Equation: Personality Traits**

Table 3.4 (column 2-8), summarises the earnings estimates accounting for personality traits. Initially, we control for individual traits and then combine them in subsequent models. The results in columns 2 through to 7 fail to find a significant association between personality traits and earnings. However, the direction of the relationships is in line with what the literature largely reports. We include the selection terms in our regression (Table B.6) and the results remain unchanged. In the previous analysis, we found that Openness, Conscientiousness and Agreeableness highly correlate; in column 8, we replace them with a principal component that captures them. We find significant association between personality traits and earnings and the result is robust to the exclusion (Table 3.4) and the inclusion of the Durbin & McFadden (1984) occupational selection terms (Table B.6). The results show a wage penalty to individuals who score high in Extraversion. A one standard deviation increase in Extraversion is associated with a 10% decrease in earnings. Our empirical results find support from a developing country study in Madagascar (Villa & Sahn, 2015); however, evidence on the relationship between Extraversion and earnings is mixed. Neuroticism becomes

significant, though it carries an unexpected positive sign. The principal component that captures individuals who are high scorers in Openness, Conscientiousness and Agreeableness positively associate with earnings. Workers defined by these traits are more likely to earn more in the labour markets.

So far, we have focussed on the average relationship between our regressors and earnings based on the conditional mean function $E(y|x)$, however, this only provides a partial view of the relationship. We take an interest in examining the relationship at different points in the conditional distribution of y (earnings) using quantile regression. Table B.3 in Appendix B, is the Mincer earnings equation regressions results at the 50th quintile (median), we also estimate another model at the 75th quantile (Table B.4). Neuroticism becomes negative, but only for the specification that excludes other personality traits variable. It remains negative in the other specifications, however, the statistical significance becomes relatively weak (at the 10% level of significance). Interestingly, regressions results at the 75th quantile suggest a negative association between neuroticism and earnings, the variable also becomes statistically insignificant. On the other hand, Conscientiousness and Openness become statistically significant, and are positively associated with earnings. The results show that returns to personality traits differ depending on one's occupation on the personality traits distribution.

We examine if sector returns to personality traits differ by interacting employment sector and personality traits (see Appendix B, Table B.5). We find significant interaction effects, suggesting differences in rewards to personality traits by sector of employment. Openness to Experience positively relates to informal sector earnings; a one standard deviation increase in the trait results in a 26% increase in earnings for individuals in informal sector occupations. Similarly, returns to Conscientiousness are high in informal employment. Looking at the coefficients, a unit increase in Conscientiousness compensates for the wage penalty of informal employment. The result highlights the importance of hard work and being organised for success in the informal sector. In particular, it shows the importance of Conscientiousness to blue collar workers' earnings (Hilger *et al.*, 2015). Interestingly, despite the negative association between Extraversion and earnings in the pooled model, Extraversion positively relates to informal sector earnings. The study reports that same positive relation for Agreeableness in informal sector employment.

3.5.3 Labour Market Mobility

So far, the study focused on the static analysis of employment outcomes. However, this gives only a partial view of the Zimbabwean labour market; we extend the analysis by looking at the employment dynamics side. We exploit the second wave of the survey to investigate employee mobility. We focus on two core aspects: identifying who moves and trying to understand why. We estimate mobility models that allow for heterogeneity in personality traits between movers and stayers.

i) Employee Mobility:

A long tradition in economics studies employee mobility in the context of standard economic variables. This study extends the analysis to the Zimbabwean adult population by including personality dispositions in mobility models. Using Subsample A (N = 663), we estimate the basic mobility model and add controls for personality traits following Equation 3.3. Table 3.6 reports the probit model marginal effects on the determinants of employee mobility. The dependent variable takes a value of one, if one left a job and zero if they stayed. Table B.7 provides a summary of the corresponding linear probability model:

Table 3.6: Probit Model Marginal effects on the probability of employee mobility

Left firm	1	2	3	4	5	6	7	8
age	-0.020*	-0.022*	-0.021*	-0.021*	-0.021*	-0.020*	-0.021*	-0.022*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
agesqr/1000	0.259**	0.279**	0.272**	0.267**	0.269**	0.257**	0.268**	0.275**
	(0.124)	(0.125)	(0.124)	(0.124)	(0.124)	(0.124)	(0.125)	(0.125)
male	-0.027	-0.037	-0.037	-0.028	-0.032	-0.023	-0.034	-0.036
	(0.049)	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)	(0.050)
married	-0.077	-0.076	-0.085	-0.077	-0.077	-0.078	-0.086	-0.085
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
yrs_educ	-0.047	-0.046	-0.049	-0.044	-0.046	-0.045	-0.047	-0.048
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)	(0.038)
educsqr	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
hhsize	0.009	0.009	0.008	0.009	0.009	0.009	0.009	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
log_tenure	-0.065***	-0.068***	-0.070***	-0.067***	-0.068***	-0.064***	-0.070***	-0.068***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
micro	0.209	0.193	0.199	0.215	0.207	0.217	0.209	0.196
	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)	(0.154)	(0.153)
small	0.113*	0.108*	0.109*	0.113*	0.111*	0.116**	0.110*	0.110*
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
medium	-0.026	-0.027	-0.026	-0.025	-0.027	-0.025	-0.024	-0.026
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Openness		0.035					-0.061	
		(0.026)					(0.079)	
Conscientious			0.063**				0.236	
			(0.031)				(0.165)	
Extraversion				0.029			0.415	-0.057
				(0.025)			(0.416)	(0.055)
Agreeableness					0.028		-0.432	
					(0.026)		(0.412)	
Neuroticism						0.017	-0.227	0.047
						(0.022)	(0.244)	(0.035)
cluster1								0.043*
								(0.024)
Num. obs.	659	659	659	659	659	659	659	659
Log Likelihood	-380.846	-379.910	-378.784	-380.141	-380.254	-380.557	-377.778	-378.54
Deviance	761.691	759.820	757.569	760.282	760.507	761.115	755.557	757.082
AIC	785.691	785.820	783.569	786.282	786.507	787.115	789.557	787.082
BIC	839.580	844.199	841.948	844.661	844.887	845.494	865.899	854.443

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: dF/dx is for a discrete change for the following variables: male, married, and firm size. Standard errors are in parentheses. Cluster1 is a principal component of the three highly correlated personality trait variables (Openness, Conscientiousness and Agreeableness).

Source: Author, 2019.

Age has a negative but diminishing effect on employee mobility. The convex relationship suggests a higher likelihood of mobility amongst young adults, which decreases with age as one approaches middle adulthood (around 43 years), beyond which it increases as one approaches retirement age. New labour market entrants are more likely to change jobs as they seek better job matches (career exploration). On the other end, old workers are more likely to exit from employment as they approach the statutory retirement age pegged at 65 years (and 60 for early retirement).

We report an inverse relation between tenure and mobility: a unit increase in tenure reduces the probability of mobility by about 6.5%. Employees with long tenure are more likely to be on permanent contracts; to them, quitting presents an opportunity cost in foregone employment security and gratuity payments. Prospects of reemployment are slim and finding a new (better) job match may be difficult, especially if skills are not easily adaptable to new roles. Taken differently, firms incur statutory retrenchment costs proportionate to one's tenure. They manage this by keeping long-serving workers, at the same time preserving firm specific human capital that come with on-the-job learning and training. Workers in small firms (10-20 workers) are more likely (11%) to move than stay, as compared to their peers in large firms (over 100 workers). Controlling for geographical location, we found that Gweru and Mutare workers are less likely to move, when compared to Bulawayo workers (not included in the table). Sector of employment, marital status, household size, years of education, and gender are insignificant in explaining mobility patterns.

ii) Personality traits and employee mobility:

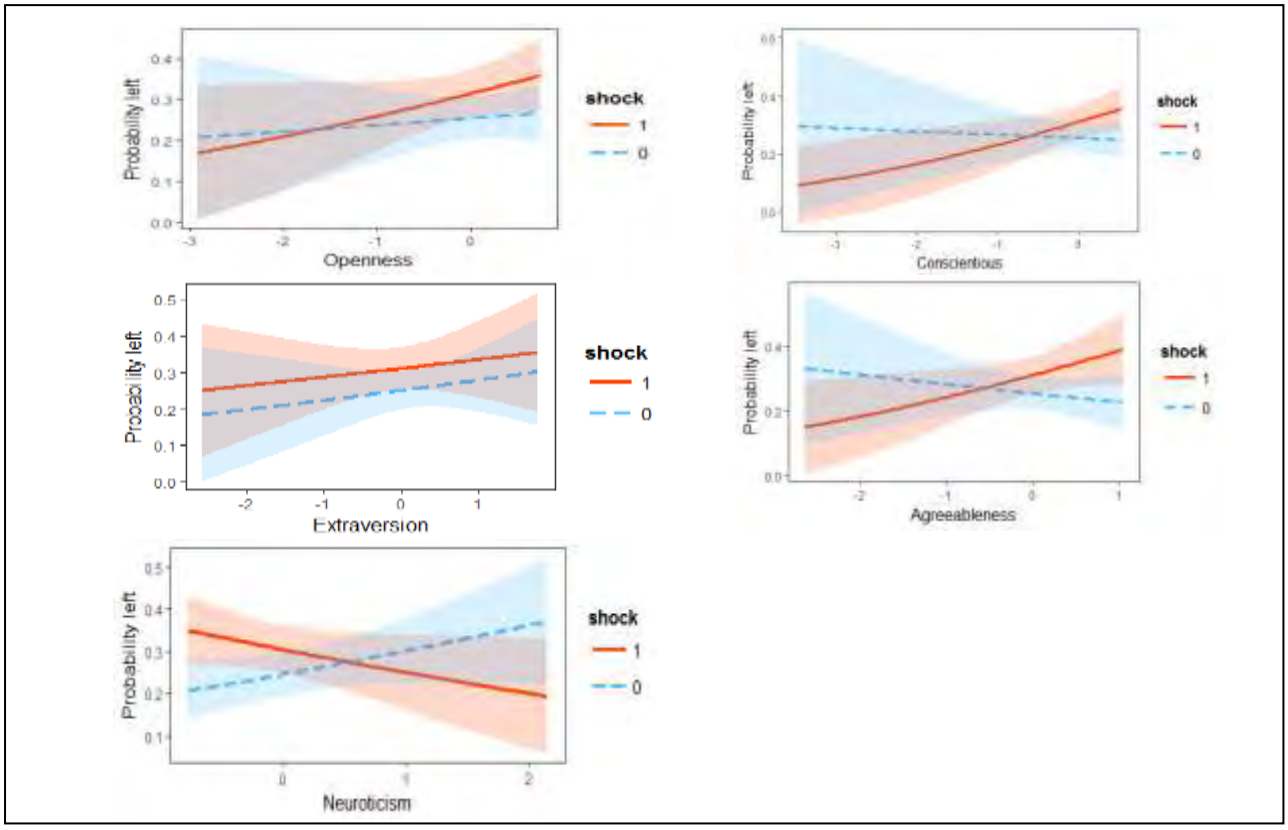
Following literature documenting that personality traits explain mobility patterns in labour markets (Van Vianen *et a*l., 2003; Zimmerman, 2008), we control for personality traits in the basic mobility equation. Table 3.6 provides a summary of the results controlling for personality traits (column 2 to 8). Highly Conscientiousness workers are - on average - more likely to move; increasing Conscientiousness by one standard deviation increases the probability of mobility by 6.3% percent, everything else being constant (column 3). In column 8, we include the principal component that captures the three correlated traits (Openness, Conscientiousness and Agreeableness). The variable weakly correlates to mobility. This result may be driven by the Conscientiousness variable, which significantly relates positively to employee mobility. The other personality trait variables insignificantly enter the mobility model.

iii) Personality Traits, Employment Shocks and Mobility:

A strand of literature argues that personality dispositions help frame ways individuals respond to shocks (Straud *et al*., 2015; Villa & Sahn, 2015). As a set of additional analyses, we investigate

whether company employment shocks influences mobility. Employment shock is a dummy variable; taking a value of one if a respondent works in a firm that recorded a drop in employment levels between 2013 and 2015. This restricts our sample (N =536) to formal sector employees. Table B.8 is a summary table of the probit model marginal effects results. The results show a positive relationship between shock and mobility. Workers in firms that experienced employment shocks have a 7.4 percent higher probability of mobility relative to those in firms that did not. This suggests that individuals' mobility patterns closely relate to company performances. In addition, marital status becomes significant, with married workers less likely to move, as compared to singles. In an environment of limited opportunities, it may be risky for married couples to move, more so because of the family responsibilities that come with marriage.

In respect of the Big Five personality traits, we largely return the same results; however, in addition, Openness to Experience becomes significant and positively explains mobility. A one standard deviation increase in Openness increases the probability of mobility by 5.4%, holding everything else constant. Following research showing that personality traits explain the ability to cope with life situations (Straud *et al.*, 2015), we extend the analysis by interacting personality traits with employment shock (Table B.11).



Note: Interaction plots are plotted using the jtools package of R, using the interact_plot function.

Figure 3.4: Interaction plots on shocks personality traits and mobility

Source: Author, 2019.

Figure 3.4 is a visual representation of the effects of personality on employee mobility, given employment shocks. The plots presents probability of mobility on the vertical axis and personality trait scores on the horizontal axis. Neuroticism becomes significant and positively relates to mobility; however, the interacted term is negative. The results suggest that highly neurotic individuals who survived earlier employment shocks are - on average - less likely to move compared to those working in firms that did not. In addition, the interacted terms for Agreeableness and Conscientiousness positively predict employee mobility. The results show that - depending on one's labour market experiences - personality traits have a moderating effect on external mobility. Conscientious individuals working in firms that experienced an employment shock have 12% more probability of mobility, compared to their peers working in firms that did not. In respect of Agreeableness, a one standard deviation increase predicts an 11% probability in mobility.

iv) Binary Choice Fixed Effects Models on External Mobility:

As part of the robustness checks, we estimate fixed effects binary choice models using the approach provided by Stammann, Heiß and McFadden implemented in the bife package of R (Stammann *et al*., 2016). We argue that there may exist firm specific (invariant) unobserved characteristics correlated with observed independent variables. We estimate firm fixed effects for the basic mobility model and specifications including personality traits variables. Table B.9 and Table B.10 present model parameters accounting for firm fixed effects. These, however are difficult to interpret, so we use *apeff_bife( )*, an inbuilt function of bife package to compute the model average partial effects. Table 3.7 summarises the probit model average partial effects. Column (a) provides estimates of the basic model, column (b) controls for all the Big Five personality traits and column (c) replaces the correlated personality variables with their principal component.

Table 3.7: Probit Model Average Partial Effects on Personality Traits and Mobility

(Dependent variable: left firm)

	(a)	**(b)**	**(c)**
age	-0.030**	-0.032***	-0.032***
agesqr/100	0.394***	0.414***	0.412***
male	-0.086*	-0.084*	-0.084*
married	-0.078	-0.078	-0.079
yrs_educ	-0.051	-0.050	-0.051
educsqr	0.002	0.002	0.002
hhsize	0.010	0.011	0.011
tenure	-0.009***	-0.009***	-0.009**
Openness		-0.023	
Conscientious		0.104	
Extraversion		0.242	-0.004
Agreeableness		0.242	
Neuroticism		-0.111	0.034
cluster1			0.013

Note: Average partial effects are sometimes referred to as marginal effects (Stammann *et al.*, 2016).

Source: Author, 2019.

After accounting for firm fixed effects, personality traits enter insignificantly into the mobility equations. This is consistent to specifications controlling for each of the five personality traits individually (not included in the table) and collectively. Age, gender, and tenure are robust to different specifications of the mobility model.

v) Personality traits and reasons for mobility:

So far, we identified who moves; it is equally important to investigate whether personality traits gravitate individuals towards voluntary or involuntary mobility. To address this, we restrict our analysis to individuals who left their jobs (Subsample B) and estimate a probit model whose binary dependent variable takes a value of one for voluntarily mobility and zero for involuntary mobility. Table 3.8 reports the probit model marginal effects, which we interpret as the effect of individual characteristics (including personality traits) on the probability of voluntary mobility relative to involuntary mobility, conditional on moving. The corresponding linear probability models results are in Table B.12.

Table 3.8: Probit Marginal effects on personality and nature of mobility

Dependent variable: left voluntarily = 1 is the base outcome

	1	2	3	4	5	6	7	8
age	-0.045**	-0.045**	-0.044**	-0.044**	-0.043*	-0.045**	-0.045**	-0.045**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
agesqr/100	0.463*	0.462*	0.451*	0.454*	0.434*	0.458*	0.446*	0.450*
	(0.240)	(0.241)	(0.241)	(0.241)	(0.242)	(0.239)	(0.247)	(0.243)
male	0.148*	0.149*	0.155*	0.153*	0.163**	0.153*	0.166**	0.156*
	(0.081)	(0.082)	(0.082)	(0.081)	(0.081)	(0.081)	(0.082)	(0.082)
married	-0.026	-0.026	-0.013	-0.027	-0.015	-0.026	-0.041	-0.051
	(0.115)	(0.115)	(0.116)	(0.116)	(0.116)	(0.115)	(0.122)	(0.119)
yrs_educ	-0.159**	-0.159**	-0.161**	-0.170**	-0.182**	-0.160**	-0.198**	-0.196**
	(0.075)	(0.075)	(0.074)	(0.077)	(0.077)	(0.074)	(0.085)	(0.082)
educsqr	0.007**	0.007**	0.007**	0.008**	0.008**	0.007**	0.008**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
hhsize	-0.012	-0.012	-0.013	-0.014	-0.014	-0.009	-0.009	-0.010
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
tenure	-0.005	-0.005	-0.004	-0.005	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
micro	0.439**	0.441**	0.446**	0.442**	0.457**	0.451**	0.432**	0.448**
	(0.191)	(0.192)	(0.188)	(0.190)	(0.184)	(0.187)	(0.196)	(0.191)
small	0.170	0.171	0.178*	0.170	0.185*	0.183*	0.175	0.176*
	(0.104)	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)	(0.108)	(0.107)
medium	0.191**	0.192**	0.191**	0.192**	0.204**	0.204**	0.219**	0.223**
	(0.085)	(0.085)	(0.085)	(0.085)	(0.086)	(0.086)	(0.088)	(0.087)
Openness		-0.004					0.360**	
		(0.053)					(0.168)	
Conscientious			-0.045				-0.596*	
			(0.075)				(0.360)	

Extraversion				-0.044			-1.657*	-0.213*
				(0.051)			(0.853)	(0.112)
Agreeableness					-0.091*		1.480*	
					(0.053)		(0.850)	
Neuroticism						0.050	0.988**	0.159**
						(0.044)	(0.500)	(0.075)
cluster1								0.066
								(0.054)
Num. obs.	195	195	195	195	195	195	195	195
Log Likelihood	-109.17	-109.17	-108.99	-108.79	-107.69	-108.55	-104.62	-106.46
Deviance	218.346	218.340	217.983	217.587	215.375	217.094	209.249	212.918
AIC	242.346	244.340	243.983	243.587	241.375	243.094	243.249	242.918
BIC	281.622	286.889	286.532	286.136	283.924	285.643	298.889	292.013

****p < 0.01, **p < 0.05, *p < 0.1*

dF/dx defines discrete change for the following variables: male, married, and firm size.

Source: Author, 2019.

We report a convex relationship between age and voluntary mobility; the probability of voluntary mobility is relatively high for young workers; it decreases, however, with age until the 50-year mark, beyond which it starts to increase. Male workers are more likely to quit voluntarily, compared to their female peers. With increasing education, the probability of voluntary mobility relative to involuntary mobility increases. Higher education signals ability, and even in an environment with constrained opportunities, these employees may particularly possess skills that are scarce and easily marketable in the job market. Workers in micro-sized and medium-sized firms are more likely to leave employment voluntarily, compared to those working for large-sized firms.

In respect of the Big Five personality traits (column 7), Conscientiousness and Extraversion negatively predict voluntary mobility, while Openness, Agreeableness, and Neuroticism positively correlate to voluntary mobility. Because of the correlations between the personality factors, the coefficients are inflated. In column 8, we control for the cluster variable that captures the correlated factors and we return the same relationship for Extraversion and Neuroticism; however, the cluster variable is insignificant.

vi) Personality traits, shocks and nature of mobility:

From the previous analysis (Table 3.8), we note that personality factors explain workers' motives of mobility. In the data description section, we argued that the two categories (voluntary vs. involuntary) might conceal vital information that increases our understanding of individuals mobility patterns. We further assess whether and to what extent personality attributes explain voluntary and different forms of involuntary mobility (retrenchments and firm closures) relative to staying. Using subsample E, we model the mobility process as a multinomial logit model, comprising of four categories: stay (base outcome), voluntary mobility, retrenched, and firm closure. The estimated coefficients are interpretable as the effect of personality traits and individual characteristics on the likelihood of being

in the three categories (voluntary mobility, retrenched, or firm closures) relative to staying. Table B.13 reports the multinomial logit estimation model estimated coefficients. In Table 3.9, we report the estimated average marginal effects from the multinomial logit model on nature of mobility for three different specifications of the model.

Table 3.9: Multinomial Logit Model Marginal effects on Employee Mobility

(Dependent variable: Left firm - with stay as the base)

	(a)			(b)			(c)		
	voluntary	retrench	closed	voluntary	retrench	closed	Voluntary	retrench	closed
age	-0.016**	-0.007	0.004	-0.016**	-0.009	0.002	-0.016**	-0.009	0.002
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
agesqr/100	0.156**	0.091	-0.031	0.161**	0.114	-0.013	0.162**	0.113	-0.012
	(0.079)	(0.085)	(0.086)	(0.080)	(0.086)	(0.086)	(0.081)	(0.086)	(0.086)
male	0.042	-0.067**	-0.009	0.044	-0.077**	-0.010	0.044	-0.080**	-0.010
	(0.034)	(0.031)	(0.030)	(0.034)	(0.032)	(0.030)	(0.035)	(0.032)	(0.030)
married	-0.043	-0.069*	0.024	-0.049	-0.067*	0.017	-0.048	-0.063	0.017
	(0.036)	(0.038)	(0.043)	(0.036)	(0.038)	(0.042)	(0.036)	(0.038)	(0.042)
yrs_educ	-0.045**	0.006	0.011	-0.044**	-0.008	0.012	-0.044**	-0.009	0.012
	(0.018)	(0.027)	(0.027)	(0.018)	(0.027)	(0.027)	(0.018)	(0.027)	(0.027)
educsqr	0.002**	0.000	-0.001	0.002***	0.000	-0.001	0.002**	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
hhsize	0.004	0.012*	-0.005	0.003	0.013**	-0.004	0.003	0.014**	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
shock	-0.007	-0.005	0.087***	-0.002	-0.004	0.092***	-0.002	-0.004	0.092***
	(0.025)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027
Openness							0.056	-0.137*	0.022
							(0.053)	(0.076)	(0.051)
Conscientious							-0.078	0.309**	0.045
							(0.109)	(0.157)	(0.102)
Extraversion				-0.041	0.060	-0.058	-0.275	0.858**	-0.010
				(0.037)	(0.041)	(0.038)	(0.269)	(0.393)	(0.260)
Agreeableness							0.250	-0.799**	-0.024
							(0.272)	(0.381)	(0.255)
Neuroticism				0.036	-0.056**	0.049**	0.173	-0.524**	0.021
				(0.025)	(0.028)	(0.023)	(0.159)	(0.230)	(0.151)
Cluster 1				0.020	-0.008	0.033*			
				(0.017)	(0.017)	(0.018)			

Note: We calculate the marginal effects in Stata using the margins command. dF/dx defines discrete change for the following variables: male, married and shock.

Source: Author, 2019.

Adding to the findings in Table 3.8, the results reinforce the idea that individual characteristics - including unobservable heterogeneity in the form of personality traits - explain the nature of mobility. We focus our discussion on column (b): individuals who score high in Neuroticism are less likely to be retrenched relative to staying; they are, however, more likely to have left a job because of firm closures. Age and education are the main non-personality trait variables, explaining voluntary mobility relative to staying. With age and education, individuals are more likely to leave employment

voluntarily than stay. Retrenchment is more common amongst female workers, as compared to their male peers. However, employees from larger households and firms that experience shock are more likely to leave because of firm closure relative to staying.

Adding controls for firm size shows that it has an effect on workers' mobility behaviour (Table B.16). For this particular model, we group the three firm size categories (micro, small and medium) as one and compare them to large firms. The resultant dummy variable - size, which takes a value of one (1) for large sized firms and zero (0) - enters significantly into our multinomial logit regression model. Workers in large firms are less likely to experience voluntary mobility relative to staying; however, they have a higher likelihood of involuntary separation in the form of closed firms than staying.

3.6 CONCLUSION

To assess the effects of personality traits on employment outcomes, we use matched employer-employee survey data collected from Zimbabwean formal and informal manufacturing sectors. We focus on the Big Five personality traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (OCEAN) to get a broader perspective of how personality traits explain individual differences in employment outcomes under conditions of economic uncertainty. To answer our main research questions, we estimate standard labour market models on sectoral selection, earnings and employee mobility, augmented with personality trait variables.

The interplay between personality traits and sectoral choice in determining employment outcomes is an important issue, especially in developing countries where the informal sector plays a significant role as a source of employment and incomes. In this study, we model the selection process as a multinomial logit model with three possible outcomes, which are mutually exclusive: formal employment, self-employment or informal employment. Our data supports that the Big Five personality traits relate to sectoral selection: workers who score high in Openness to Experience, Agreeable, and Neurotic individuals are more likely to be in informal sector labour markets. On the contrary, those who score high in Conscientiousness and Extraversion are more likely to select into formal employment. In terms of earnings, personality traits indirectly influence earnings through endogenous sectorial selection. However, significant interacted effects highlight that returns to personality traits are sector specific. In particular, personality traits (Conscientiousness and Extraversion) exhibit positive and significant returns for those engaged in informal sector employment.

In respect of mobility, personality traits interact with employment shocks to explain individual mobility patterns. In addition, they explain individuals' motives of mobility. The findings shed insights into individuals' decision-making processes when confronted with novel situations. While empirical literature reports that highly Conscientious and Agreeable individuals are more likely to experience job satisfaction and value contractual obligations, we provide evidence showing that employment shocks reverse the effects of these traits. The literature argues that Agreeable individuals - for

instance - are understanding in nature, and may feel obliged to give back to the firm (and team) by being loyal. While this may be true for individuals working in well performing companies, our results show that given employment uncertainty (from past employment shock), these individuals are on average more likely to move.

This research finds strong support for accounting for behavioural variables in modelling labour market outcomes. Psychological traits such as the Big Five personality traits have significant effects on sectoral selection, earnings, and employee mobility. As research continues to examine the role of human capital in explaining economic outcomes, these findings suggest that the exclusion of personality variables in standard labour markets models may leave out important information that increases our understanding of the sources of individual differences in economic outcomes.

CHAPTER 4

RISK PREFERENCES AND JOB MOBILITY IN ZIMBABWE

ABSTRACT

Job mobility is a fundamental characteristic of labour markets. The decision to move from one job to another is inherently risky. This is particularly so because workers have limited information regarding the quality of outside jobs. Canonical models on job mobility assume risk neutrality; however, risk aversion potentially affects workers' mobility decisions thorough influencing job acceptance (reservation match quality) and job search (search effort). This paper integrates concepts from the risk and job mobility literatures to investigate the empirical relationship between risk aversion and job mobility in an economic environment characterised by uncertainty. To answer this important question, we use the Zimbabwean matched employer-employee panel data set (2015-2016), which includes experimentally elicited risk preferences measures. Our empirical approach involves estimating the basic mobility model using the traditional economic variables and controlling for individual heterogeneity in risk preferences. Our results show that risk aversion explains job mobility; risk tolerant workers are more likely to experience job mobility compared to their risk averse peers. This relationship is robust to the inclusion of human and job characteristics known to explain job mobility. The study broadens our understanding of employment dynamics in developing countries' characterised by economic uncertainty. Furthermore, it contributes to the recent debate on how heterogeneity in risk preferences explain variations in economic outcomes, in particular those related to labour markets.

Keywords: Risk aversion, job mobility, uncertainty

4.1 INTRODUCTION

Risk and uncertainty are central in almost every important aspect of economic decision-making. This is particularly true in labour markets where workers decide between staying and moving to another job. Job mobility is fundamental to the efficient functioning of labour markets (Mortensen, 2011); as such, knowledge of how workers make decisions related to moving between jobs is important. The drivers, and subsequent positive effects of job mobility on wages has been explored by theoretical models (e.g. Burdett, 1978; Johnson, 1978; Jovanovic, 1979) and largely supported by empirical literature (Fuller, 2008; Neumark, 2002; Pavlopoulos *et al*., 2014; Topel & Ward, 1992). Existing theoretical models on job mobility possibly miss some important information on workers' job changing behaviour, as they assume homogenous risk preferences and concentrate on observable individual and job characteristics. Recently, interest has grown in identifying additional measures that could explain employee mobility. A major issue addressed in this literature is the role of risk preferences (Argaw *et a*l., 2017; van Huizen & Alessie, 2016; Vardaman e*t a*l., 2008).

Following a study in the Netherlands by van Huizen & Alessie (2016), we empirically examine how risk preferences influence job mobility under conditions of economic uncertainty. Job changes are risky and involve uncertainty. Van Huizen & Alessie (2016) derive predictions on the relationship between risk aversion and job mobility, through two main channels: job search and job acceptance. Even after accounting for anticipated costs and benefits of job mobility, a worker's benefits from a job change are not fully determined *ex ante*. We argue that individuals' willingness to take risk is key in explaining job mobility behaviour in the labour market. In order to throw light on these matters, the study presents new data on risk preferences from a developing country characterised by economic uncertainty. The novel matched employer-employee panel data set from the Zimbabwean manufacturing sector contains information on individuals' labour markets experiences and a range of background characteristics. In addition, it contains information on individuals' risk preferences elicited through incentivised lab-in-the-field experiments.

Empirical evidence on the role of risk preferences in explaining mobility decisions under conditions of economic uncertainty - within a developing country context - is virtually non-existent. To our knowledge, a few studies empirically examine the effects of risk aversion on job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016; Vardaman *et al*., 2008). However, except for Falco (2014), who investigates occupational sorting, existing literature is biased towards developed countries whose labour markets differ remarkably from developing countries. Some of the studies rely on survey types of measures (Argaw *et al.*, 2017), as well as hypothetical lotteries to capture individuals risk attitudes. While convenient, hypothetical gambles hinge on the assumption that subjects have knowledge of how they would behave in real world situations where they have to make choices, and that they have no motive to hide their true preferences (Kahneman & Tversky, 1979). This may not always be the case. We address these issues by presenting subjects with incentivised 'simple choice tasks', designed to capture risk attitudes.

A critical step in investigating the role of risk preferences in workers' mobility decisions involves developing empirically valid measures of risk preferences. In this study, we follow previous literature (Cramer *et al*., 2002) and adopt the Arrow-Pratt (Pratt, 1979) measure of absolute risk aversion to estimate individuals' risk aversion. As an initial step, we check for sources of heterogeneity in risk preferences by a set of standard demographic characteristics. We establish that risk preferences vary by one's sector of employment, their ethnicity, and geographical location. The study turns to a more systematic regression-based type analysis of the relationship between risk preferences and job mobility. We estimate the standard mobility model and control for risk preferences. In line with our hypothesis, we find that risk averse workers are less likely to experience job mobility. Previous studies also confirm this relationship (Argaw *et al*., 2017; van Huizen & Alessie, 2016). The results suggest that models that seek to describe observed labour market flows should allow for individual heterogeneity in risk attitudes.

The study contributes to the recent debate on how heterogeneity in risk preferences explain variations in individuals' economic outcomes, in particular those related to labour markets. Employee mobility is an important variable in labour economics, as it relates to wages and careers (Pavlopoulos *et* al., 2014; Pfeifer, 2010; Topel & Ward, 1992); the results thus have important implications on individuals' labour market success. Given the recent interest in exploring the risk aversion - job mobility nexus and subsequent wage growth (Argaw *et al*., 2017) - the study offers new insights on the possible mechanisms constraining or aiding income growth in developing countries.

In addition, it broadens our understanding of the literature on labour market dynamics in countries characterised by economic uncertainty. Focusing on Zimbabwe makes it a particularly interesting case. Zimbabwe is currently going through one of its worst and prolonged periods of economic challenge. Amongst the most adverse and enduring effects of decades of Zimbabwe's economic malaise is the increase in long-term unemployment and the simultaneous contraction of the formal sector and the expansion of the informal sector (ZIMSTAT, 2015). Unlike developed countries that typically have tight labour markets, alternative job offers are difficult to find in an economically struggling country like Zimbabwe. Given these economic conditions, quitting a job may be significantly risky, as the likelihood of becoming unemployed while queuing for job offers is high. On the other hand, the relatively free entry informal sector is equally associated with income uncertainty (Bennett *et al*., 2012a; Falco, 2014). Unsurprisingly, a significant portion of the worker sample (40%) report being owed (outstanding salaries) by their firms but continue to report for work. This may imply that to these individuals quitting a job (even a bad one) is more risky than staying. Empirical evidence shows that being unemployed for a long time comes with an emotional toll, especially for married men (Basbug & Sharone, 2017). For these reasons, risk aversion may be a critical factor in explaining labour dynamics in developing countries.

We structure the remainder of the study as follows: Section 4.2 to 4.4 discusses job mobility theories, findings from previous literature, and spells out the conceptual framework. We discuss the data and methodological framework adopted in this study in section 4.5. Section 4.6 reports the results from the probit model estimation of the effects of risk aversion on job mobility and discuss the findings. Section 4.7 and Section 4.8 discusses findings and concludes respectively

4.2 THEORETICAL MODELS ON EMPLOYEE MOBILITY

In labour economics, on-the-job-search and job matching models form the theoretical basis of studying job mobility. Individuals search for jobs and accept offers when the value (wage) of the new job is higher than the present job (Burdett, 1978; Jovanovic, 1979). In essence, workers transition between jobs to improve their current situation. The predictions of search models imply lower job transitions with increasing age, as workers are more likely to have searched and found better jobs. Hwang *et al.* (1998) introduce non-wage components in the on-the-job search framework, signifying the importance of job characteristics. These characteristics include hours worked, working time, work

environment, and employment conditions. Subsequent empirical analyses confirm the importance of non-wage job characteristics on individuals' decision to change jobs (Baird, 2017; Bonhomme, Jolivet & Leuven, 2016; Sullivan & To, 2014).

The principal concern of this literature was to account for the role of observable human and job characteristics in explaining individuals' job changing behaviour. The models have undoubtedly increased our understanding of job mobility; however, they may not adequately explain observed differences in mobility patterns amongst workers, especially in developing economies. Central to these models is the premise of imperfect information; in most instances, the quality of job match only reveals itself sometime after the employee has accepted a job offer. Topel & Ward (1992) show that most job transitions in the early career (often job-to-job) reflect voluntary job changes rather than layoffs. There are "search or information frictions" in the labour market that prevent workers from immediately matching with their optimal job. Even after accounting for foreseen costs and benefits of job mobility, a worker's benefits from a job change are not fully determined *ex ante*. Changing one's job - especially outside of the present firm - is inherently risky. Workers' risk aversion is thus an important factor when evaluating the expected utility from a job switch. Hence, *ceteris paribus*, risk tolerant individuals are more likely to experience job mobility, because these individuals are more willing to take risk associated with a job change.

4.3 PREVIOUS LITERATURE

A significant amount of literature focuses on developing empirically validated measures of individuals' risk attitudes (Holt & Laury, 2002, 2014; Lönnqvist *et al*., 2015; Thomas, 2016). This has broadened our appreciation of dimensions of individuals' unobservable heterogeneity[15]. However, questions remain. One important question relates to the determination of individuals risk attitudes, using experimentally elicited measures involving real monetary payoffs, in the context of developing countries. Some studies rely on survey types of questions, typically self-ratings on a Likert scale (Dohmen *et al*., 2010), while others rely on hypothetical gambles. Because these methods are not incentive compatible, there is scepticism on whether they capture individuals' truer attitudes to risk. A number of factors could possibly distort individuals' reported risk attitudes, including self-serving biases and inattention (Camerer & Hogarth, 1999). To address these concerns, incentive compatible experimental measures have been developed (Holt & Laury, 2002, 2014), and are often regarded as the gold standard in measuring risk aversion.

Theoretical models on labour markets are silent on individuals' attitudes to risk, or assume that workers are risk neutral. However, emerging literature documents the significance of risk preferences in explaining a variety of life outcomes (including health, migration, education, and labour market outcomes). Labour market studies have focused on selection into self-employment (Ahn, 2010;

[15] Other measures include personality traits and time preferences.

Caliendo *et al*., 2009; Ekelund *et al*., 2005; Skriabikova *et al*., 2014), sectorial choice (Falco, 2014), and occupational choice (Fouarge *et al*., 2014). Others highlight choice of employment contract (Dohmen & Falk, 2011), job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016) and earnings (Bonin *et al*., 2007; Cho, 2012; Kim & Lee, 2012). Evidence from these studies shows that differences in risk attitudes have considerable effects on labour market outcomes.

Studies on selection into self-employment report that risk tolerant individuals are most likely to be self-employed (Ahn, 2010; Caliendo *et al*., 2009; Ekelund *et al.*, 2005; Skriabikova *et al*., 2014). In respect of earnings, the empirical literature largely reports a wage premium for risk-loving individuals (Ahn, 2010; Bonin *et al*., 2007). The wage premium has been confirmed to be robust to controls for heritability and family background variables (Le *et al*., 2014). In addition to the direct effect on earnings, risk aversion has an indirect effect on wages through occupational choices. Risk averse individuals are more likely to work in the formal sector (Bennett *et al*., 2012a; Ekelund *et al*., 2005; Falco, 2014). Furthermore, there is evidence that confirms that risk attitudes account for gender differences in labour market outcomes, for instance Le *et al*., (2010) found that it accounts for some of the gender wage gap.

Literature on the effects of risk aversion on job changes is scarce. We only know of few studies that model the relationship between risk attitudes and job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016; Vardaman *et al*., 2008). Using German data, Skriabikova *et a*l. (2017) developed risk preference measures based on survey questions, and found that risk seeking individuals were more likely to experience job mobility. The study further reported that subsequent wage growth arising from job switches was lower for risk tolerant individuals, as compared to those that were risk averse. In a related study, van Huizen & Alessie (2016), using a Dutch panel, found similar results. Risk aversion inversely relates to job mobility. The study, however, reported stronger effects for the sample treated to an incentivised experiment, as compared to those who participated in an experiment with hypothetical payoffs. The finding suggested that incentives helped eliminate some of the noise in the risk measure, which has important implications in empirical analysis. In addition, they reported that risk aversion (particularly) has a stronger effect on job mobility for workers on permanent contracts and under tougher economic conditions. Despite using different risk measures, both studies report similar results and offer insights on the importance of accounting for risk attitudes in mobility models.

What is clear from the literature is that work on the effects of risk aversion on job mobility is still developing; more so, it is particularly non-existent for developing countries (especially in Sub-Saharan Africa). It is surprising that this literature is scarce in respect of developing countries, yet risk preferences may be crucial in explaining the remarkable differences in labour market success in these countries. For instance, empirical evidence shows that risk aversion may result in economic agents foregoing better economic opportunities (Van den Berg *et al*. 2009) and may slow down the process of economic recovery after a negative economic shock (Dohmen *et al*. 2016). Given the

importance of risk attitudes in explaining life outcomes, the study aims to addresses the empirical vacuum first by determining workers risk attitudes. We then extend the analysis to Zimbabwean labour markets, focusing on observed workers' job changing behaviour.

4.4 CONCEPTUAL FRAMEWORK

In this study, we adopt van Huizen & Alessie (2016) theoretical model that formalises the relationship between risk aversion and job mobility. The model explains two potential channels through which risk aversion influences job mobility: job acceptance (Jovanovic, 1979) and job search (Burdett, 1978).

4.4.1 Risk aversion and job acceptance

Van Huizen & Alessie (2016) model builds on Jovanovic (1979), and argues that individuals possess more information about their current job compared to outside opportunities. To capture the notion of *ex ante* uncertainty of the quality of job match, their model assumes that at any given point in time a job offer y arrives as a random draw from the joint distribution $\mathrm{F}(y)$, where $y \sim N(\mu, \delta_{\mu}^{2})$. Unlike in the canonical on-the-job-search, the value of the job match is not simplified to the (known) wage, but contains non-wage job characteristics (Sullivan & To, 2014) that determine the (dis)utility derived from holding the job. When a job offer arrives, a worker does not observe the true value of the job. He, instead, receives a noisy signal $\hat{y} = y + \varepsilon$, where $\varepsilon \sim N(0, \delta_{\varepsilon}^{2})$.

Once job offer is received, a worker decides between taking up the job and rejecting it; worker accepts job only if his valuation of the job $(\hat{y})$ is greater than the reservation match quality $\hat{y}^{*}$. His point of indifference is defined by:

$$V(y_0) = E[V(y)|\hat{y} = \hat{y}^{*}] \quad \text{.....(4.1)}$$

where $V(y_0)$ defines utility derived from current job match y_0 and $E[V(y)|\hat{y} = \hat{y}^{*}]$ is the expected utility value of the reservation match quality $\hat{y}^{*}$. Workers evaluate the expected utility of the new job match differently according to their risk attitudes. Because of the uncertainty of outside jobs, risk averse workers take a precautionary stance in evaluating job offers, compared to risk neutral workers:

$$E[V(y)|\hat{y} = \hat{y}^{*}] = V[E(y|\hat{y} = \hat{y}^{*}) - \Pi] < V[E(y|\hat{y} = \hat{y}^{*})] \quad \text{.....(4.2)}$$

where Π indicates the risk premium. The link between risk attitudes and reservation match quality can be examined using the following equations:

$$E[V(y)|\hat{y} = \hat{y}^{*}] = V[E(y|\hat{y} = \hat{y}^{*}) - \Pi] \cong V[E(y|\hat{y} = \hat{y}^{*})] - \Pi V'(E(y|\hat{y} = \hat{y}^{*})) \text{..... (4.3)}$$

$$E[V(y)|\hat{y} = \hat{y}^{*}] \cong V[E(y|\hat{y} = \hat{y}^{*})] + \frac{1}{2}E(\tilde{\varepsilon}^{2}|\hat{y} = \hat{y}^{*})V''\big(E(y|\hat{y} = \hat{y}^{*})\big) =$$

$$V[E(y|\hat{y} = \hat{y}^{*})] + \frac{1}{2}\frac{\sigma_{\varepsilon}^{2}}{\sigma_{y}^{2}+\sigma_{\varepsilon}^{2}} V''\big(E(y|\hat{y} = \hat{y}^{*})\big) \quad \text{.....(4.4)}$$

We can derive the function for the risk premium:

$$\Pi = \frac{1}{2}\frac{\sigma_\varepsilon^2}{\sigma_y^2+\sigma_\varepsilon^2} A_{\hat{y}^*} \quad \text{(4.5)}$$

Note that equation (1) and (3) imply that:

$$y_0 = E(y|\hat{y} = \hat{y}^*) - \Pi \quad \text{(4.6)}$$

Using equation 5, equation 6 can be written as[16]:

$$y_0 = E(y|\hat{y} = \hat{y}^*) - \frac{1}{2}\frac{\sigma_\varepsilon^2}{\sigma_y^2+\delta_\varepsilon^2} A_{\hat{y}^*} \quad \text{(4.7)}$$

Under the assumption of normality of y and ε, we can express the reservation match quality:

$$\hat{y}^* = y_0 + \frac{\sigma_\varepsilon^2}{\sigma_y^2}\left[y_0 - \mu_y + \frac{1}{2}A_{\hat{y}^*}\right] \quad \text{(4.8)}$$

Equation 4.8 shows that individuals' reservation match quality ($\hat{y}^*$) increases with risk aversion ($A_{\hat{y}^*}$); risk tolerant workers change their jobs more often, compared to risk averse workers. The job acceptance decision dictates that a worker accepts a job when the signal from the job offer is greater than the reservation value ($\hat{y} > \hat{y}^*$). The significance of risk aversion in job acceptance depends on the noise of the signal (δ_ε^2); if quality of match is perfectly observable ($\delta_\varepsilon^2 = 0$), job mobility will be riskless and involves no uncertainty.

In addition to this, there is a direct relation between current job match and reservation match quality. The implication is that workers in better matches are more likely to stay compared to those in bad matches. The uncertainty in the value of alternative matches (captured by σ_y^2) reduces the reservation match value if the current job match is low (when $y_0 - \mu_y$ is sufficiently negative), but increases the reservation value if the current job match is sufficiently high. Uncertainty may thus have two effects, depending on current match: encourage workers in bad jobs to quit, and discourage those in good jobs from leaving.

4.4.2 Risk aversion and job search

The model focused on so far assumed that job offers are exogenous; however, search intensity determines job arrival rates. Search activities require one's commitment in terms of time and effort, and may be stressful. Theoretically, on-the-job search S involves costs $c(s)$, defined by an increasing convex function of s, and determines job arrival rates λs, where λ captures efficiency of search. A worker sets an optimal job search effort by equalising marginal costs of search ($c'(s)$) with marginal benefits of search:

[16] $E(y|\hat{y} = \hat{y}^*) = \frac{\sigma_\varepsilon^2}{\sigma_y^2+\sigma_\varepsilon^2}\mu_y + \frac{\sigma_y^2}{\sigma_y^2+\sigma_\varepsilon^2}\hat{y}^*$

$$c^{'}(s) = \lambda E\int_{\bar{y}^*}^{\bar{y}}\left[V(y)-V(y_0)\right]dF(y) = \lambda\left[1-F(\hat{y}^*)\right]\left[E\left(V(y\mid\hat{y}^*)\right)-V(y_0)\right] \quad \text{.....(4.9)}$$

If we assume risk aversion does not affect reservation match quality ($\hat{y}^*$), search intensity is less for risk averse workers than for risk neutral workers such that;

$$[1-F(\hat{y}^*)]\left[E(V(y|\hat{y} > \hat{y}^*)) - V(y_0)\right] < [1-F(\hat{y}^*)]\,[V(E(y|\hat{y} > \hat{y}^*)) - V(y_0)] \quad \text{.....(4.10)}$$

The intuition behind this is that risk averse individuals are reluctant to invest in job search, since it comes with uncertain rewards. As shown in Subsection 2.2.1, upon receiving an offer, the reservation match quality increases with risk aversion. In equation 4.10, we also discovered that risk aversion decreases search intensity and thus the probability of a successful search. This, therefore, reduces the marginal gains of search. If we consider two individuals, one who is risk loving ($A^L_{\hat{y}^*}$), and the other who is risk averse ($A^H_{\hat{y}^*}$), equation 4.8 implies that, given a job offer, a risk averse worker is more critical of the job offers ($\hat{y}^*_H > \hat{y}^*_L$), and therefore is more likely to reject a job offer. This suggests a decrease in marginal gains from search:

$$\lambda E\int_{\hat{y}^*_L}^{y}[V(y)-V(y_0)]\,dF(y) =$$

$$\lambda E\int_{\hat{y}^*_L}^{\bar{y}}[V(y)-V(y_0)]\,dF(y) + \lambda E\int_{\hat{y}^*_H}^{\bar{y}}[V(y)-V(y_0)]\,dF(y) > \quad \lambda E\int_{\hat{y}^*_L}^{y}[V(y)-V(y_0)]\,dF(y) \quad \text{.....(4.11)}$$

Hence, risk aversion potentially influences job mobility through two channels: it reduces investment in jobs search chiefly because benefits of search are uncertain, and it lowers expected gains from search activities, as risk averse individuals are more likely to turn down potential offers.

4.4.3 DISCUSSION

The theoretical model sheds insights into the link between risk aversion and job mobility; however, it does not spell out some of the factors that are pertinent in the mobility process (van Huizen & Alessie, 2016). We discuss some of the factors that we think are relevant to the Zimbabwean context. The model assumes that job mobility is risky; however, this may not always be the case. Generally, the current job match is expected to offer more protection than the alternative match. This is because firms incur firing costs in form of statutory retrenchment packages and severance pay whenever they lay-off workers. The cost may be significant if a worker has longer tenure, as it is proportionate to one's tenure. However, depending on the nature of the employment contract, there may be uncertainty in the current job. Employees on permanent contracts may be more certain about their security of employment compared to those on temporary contracts. Quitting a permanent job may not only mean forfeiting a secure job, but also the associated employment benefits which typically increase with tenure. Among this group, quitting a job may be riskier than staying. This may, however, not be the case for those in temporary jobs as staying may present more uncertainty when

compared to moving. The probability of job retention is typically low for workers on temporary contracts, compared to those on permanent contracts. Our worker sample reports the nature of one's employment contract; in this study, we empirically examine if risk aversion matters more for workers on a permanent contract.

Secondly, a worker's ability to mitigate negative effects of job mobility - if a new match proves to be poor - may be relevant. As such, labour market conditions may dictate the extent to which risk aversion affects job mobility. Unlike developed countries that have tight labour markets, developing countries (and Zimbabwe in particular) offer little to no alternative jobs once one leaves his/her current employment. Related to the previous point on the certainty of a current job is firm performance: in particular, firm employment shocks may bring about uncertainty in the current job. In a tight labour market, if a firm is struggling, even risk averse individuals' may leave their current employment as the risk of staying may be high (compared to that of moving). The 'sink or swim' relationship is, however, ambiguous, in respect of developing countries where outside options are limited. We examine if there is a difference in effect between workers that work in firms that experienced employment shocks and those that did not.

4.5 Data and Methods

To test the empirical relation between risk preferences and job mobility we rely on the MEPLMAZ, a representative data set that captures firm and worker information from the Zimbabwean manufacturing sector. It captures information from both formal and informal manufacturing firms and workers, covering seven main industrial sub-sectors. The existing two waves of the survey (2015 - 2016) form the basis of our analysis. Wave 1 contains simple incentivised experiments that measure a set of economic preferences central in capturing individual behaviour in economic choices. Despite the fact that economic theory abstracts away from details of economic preferences, they explicitly model preferences over certain attributes: timing and risk, for instance, that are typically relevant in economic decisions. Economic preferences can be broadly classified under three main dimensions: time, risk, and social preferences (Golsteyn & Schildberg-Hörisch, 2017). Risk preferences define how much risk one is willing to take in the presence of uncertainty.

In this study, we follow the revealed preference paradigm, which infers preferences from choices based on incentivised experiments[17]. Subjects to an experiment receive a monetary reward in line with their choices. The benefits of incentivised experiments is that they allow for choices reflective of real life situations that can be observed for different individuals (Falk *et al*., 2016). Determining measures of these economic preferences, therefore, lays an important foundation for examining their role in explaining economic outcomes, including those related to labour markets.

[17] Following traditions in psychology, economists have also developed non-incentivised measures that rely on self-reports in the form of a questionnaire. An example is the risk preferences measure in the German Socio Economic Panel (SOEP) data, which rates individuals' preferences on a 11 point Likert scale (Dohmen *et al.*, 2011b).

The MEPLMAZ elicits risk preference measures based on incentivised choice experiments. Experimental elicitation of preference measures is generally expensive to implement in representative samples, compared to survey measures. In ideal situations, the experimental setup encompasses a large menu of lotteries (like in the case of Holt & Laury, 2002), but this may be costly when one is faced with both time and financial constraints. To allow for choices that reflect individuals' risk attitudes in a multi-module survey, our experiment involves real monetary payoffs[18], and the experimental design aims at minimising both time and financial costs.

The 2015 wave of the survey contains a novel set of questions that constitute the experiment. It randomly assigns subjects to either the risk or time preferences experiment. This resulted in 860 and 799 workers participating in the risk and time choice experiments respectively. For now, we focus on the risk subsample. To ensure that the outcomes are randomised, the experiment randomly assigned subjects to different prized lotteries, valued between US$2 and US$7. By varying the lottery amounts, the experiment seeks to have an idea of how choices change with lottery prices. This is also ensures that the choices are incentive compatible. The random generator was coded in a way that sought to optimise the available financial resources while guaranteeing that subjects' choices reflect their risk attitudes. Subjects chose between participating in a gamble with higher stakes, or abstaining and getting a sure but lower amount. The risk elicitation task was structured as follows:

> *As a token for participating, we would like to give you some airtime credit. Either, we can transfer US$2 to your phone tomorrow or you can play a game for more money. If you win, you will get US$X (US$2 to $7) but if you lose, you will get nothing. You have an equal chance of winning or losing. Which one would you like? How much money will make you want to play the game. Note: enter 999 if person does not play these types of games (e.g. for religious reasons). What amount would make you rather take the $2 for sure?*

From the experiment, we gathered information on individuals' lottery choices and the associated reservation prices. We begin by summarising the raw data to learn how risk choices vary across individual respondents.

4.5.1 Risk preferences subsample

Table 4.1 presents the choices of the subjects. The table summarises the experimental setup by risk options offered, disaggregating between individuals who took the safe option and those who chose the gamble. The majority of the workers chose the US$2 sure option (i.e. chose not to play the gamble) - 730 (84.9%) - while the rest - 130 (15.1%) - took the gamble. Furthermore, the data shows that, with increasing payoffs, more individuals are attracted to participate in the gamble.

[18] The monetary amounts (between US$ 2-7) were big enough to motivate individuals to behave in a way that reveals their true risk and time preferences. The worker survey took at most 15 minutes to administer, and as such going by individuals' hourly wages (just less than US$2) the amounts were significantly higher than one's average 15 min pay. In addition, in the time preference task, a larger proportion took higher amounts even though they came with a time delay.

Table 4.1: Summary of the risk choice options

Gamble Amount	Expected payoff	No' of workers	Safe option	Gamble	*p-value*
2	1.00	19	16 (84.2%)	3 (15.8%)	0.102
3	1.50	100	91 (91%)	9 (9%)	0.000
4	2.00	234	207 (88.5%)	27 (11.5%)	0.000
5	2.50	175	146 (83.4%)	29 (16.6%)	0.000
6	3.00	210	173 (82.4%)	37 (17.6%)	0.000
7	3.50	121	96 (79.3%)	25 (20.7%)	0.000
Total		**860**	**730 (84.9%)**	**130 (15.1%)**	

NB: expected payoffs is the lottery price multiplied by the probability of winning (p=0.5). An error in the coding resulted in 19 subjects being assigned to a US$2 lottery, this was however rectified after being taken note of.

Source: Author, 2019.

The survey further probes subjects about the amounts that would make them reverse their initial choices - their reservation prices. This is an important piece of information in computing the risk aversion measure. Figure 4.1 classifies the respondents' reservation prices for those that took the gamble (panel a) and those that chose the safe option (panel b), averaged for different lottery options offered to subjects. The blue line summarises the amounts that are acceptable for one to take the gamble, and the red line represents amounts that would rather make individuals take the sure amount.

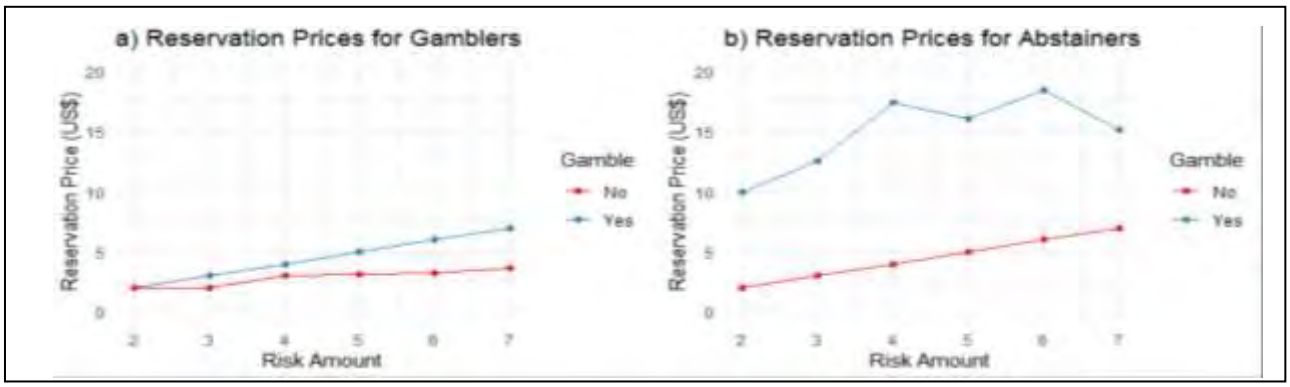


Figure 4.1: Workers' average reservation prices per given lottery

Source: Author, 2019.

In panel (a), for example, subjects who accepted the US$5 gamble would only abstain from the gamble and take the sure amount (US$2) if the gamble amount falls to an average of US$3. On the other hand, in panel (b), subjects who turned down a US$5 gamble for a sure amount of US$2 required more than double the amount (at least US$16) to tempt them into participating in the gamble. In summary, the data shows that higher amounts induce subjects to take up the lottery, while lotteries closer to the sure amount (i.e. with an expected payoff less than US$2) tempt them to abstain from the gamble.

4.5.2 Characteristics of individuals' gamble choices

As part of the descriptive statistics, we take an initial interest in understanding subjects' choices in the risk experiment. To do this, we estimate a probit model on individuals' likelihood of participating in the gamble as a function of a number of variables (socio-economic and demographic characteristics) thought to influence individuals gambling decisions. Table C.1 is a summary table of the probit model marginal effects, the dependent variable - gamble - is binary and takes a value of one if one participated and zero otherwise. The results show that the amount of the gamble positively correlates to gamble participation. Age inversely relates to gamble participation; however, the inclusion of other variables makes the relationship statistically insignificant. With higher education, the likelihood of gamble participation increases. Other factors such as wage, sector, and gender enter insignificantly into the equation. While the expectation is that gender influences gambling decisions, our model fails to provide supporting evidence. Our sample is predominantly male (81%), which could explain this.

4.5.3 Measuring Risk Preferences

The first question this Chapter aims to answer relates to the nature and distribution of risk preferences amongst a sample of the Zimbabwean manufacturing sector workers. In measuring risk preferences, we make a crucial assumption that subjects take the experiment in isolation of their constraints, or circumstances, outside the experiment. We rely on the unique feature of our data: it directly captures subjects' lottery prices as well as their reservation prices. Given this, we use the Arrow-Pratt[19] approximation to measure individuals' risk aversion. We follow Cramer *et al*. (2002) and specify the measure of absolute risk aversion as below:

$$\rho = \frac{\alpha Z - \lambda}{(\lambda^2/_2 + \alpha Z^2/_2 - \alpha\lambda Z)} \quad \text{.....} \quad (4.12)$$

where Z is the lottery prize, α the probability of winning the lottery (0.5), and λ an individual's reservation price, or minimum amount that would tempt them to reverse their gamble choice. For individuals who participated in the gamble, the lottery price is the gamble amount offered and the participants directly report the reservation price. This however is not the case for individuals who abstained from the gamble; their lottery price is the amount that would induce them to play the gamble and their reservation price is the lottery price offered in the experiment (refer to Figure 4.1). An Arrow-Pratt value $\rho < 0$ indicates risk-seeking behaviour, $\rho = 0$ signals risk neutrality and $\rho > 0$ shows risk aversion.

We use the risk preferences data to compute the Arrow-Pratt risk measure; we report a mean value of -0.109 with a standard deviation of 0.224. The data shows that an average participant exudes

[19] Cramer *et al.*, (2002) provides a detailed derivation of the measure of absolute risk aversion from Arrow-Pratt's (Pratt, 1964) original formulation based on the common utility functions ($\rho = \frac{-U''}{U'}$). We adopt this formulation for the purpose of our present analysis.

risk-seeking behaviour. In Figure 4.2, we examine the distribution of individuals risk attitudes for male and female participants, disaggregated by their occupational sector, using density plots. The density plots, however, show something interesting; most of the participants score just above zero and, as such, a few individuals who exude extremely risk-seeking behaviour might be behind the negative mean:

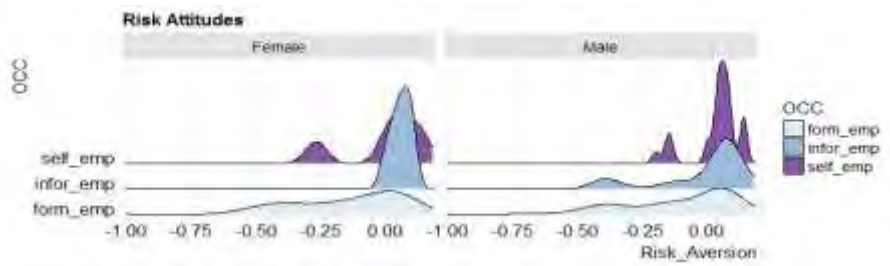


Figure 4.2: Distribution of individuals risk attitudes by gender and occupational sector

Source: Author, 2019.

4.5.4 Characteristics of individuals' risk preferences

To help unpack the nature and sources of variation in individuals' risk aversion, we relate our risk aversion measure to a set of individual demographic and geographic variables, proposed as potential covariates of risk preferences in the empirical literature. The estimates of relationship between the Arrow-Pratt measure of risk aversion and individual demographic characteristics using OLS regressions is presented in Table C.2. The results are raw correlations; however, they speak to what previous literature has articulated and hypothesised (Borghans *et al*., 2009; Dohmen *et al*., 2010; Falk *et al.*, 2018; Wik *et al*., 2004). We find that workers' risk attitudes differ by one's sector of employment, geographical location, and ethnic group. On average, informal sector workers are more risk averse than formal sector workers. Regarding geographical location, Bulawayo-based employees are more risk loving, as compared to those from other regions of the country and the relationship is robust to the inclusion of an ethnic variable. The other demographic characteristics that typically correlate with risk preferences (age and gender) enter the regression equation insignificantly. Empirical results from similar economies largely report females to be more risk averse, compared to males (Wik *et al*., 2004); we, however, fail to establish this in our study. The result is unsurprisingly as the sample is predominantly male. Despite literature largely reporting increasing risk aversion with age (Borghans *et al*., 2009; Falk et al., 2018), some studies also report an insignificant relation (Abreha, 2007; Senkondo, 2000).

4.5.5 Estimating employee mobility

The main empirical question this study seeks to answer is whether heterogeneity in risk aversion explains job mobility amongst a sample of Zimbabwean workers. We use the existing two waves of the survey to answer this important empirical question. The first wave contains the main variable of interest as well as covariates that feed into the regression model. The second wave provides the job

mobility variable. In the previous Chapter, we estimated individuals' mobility patterns and control for personality traits; in this paper, we extend the analysis by controlling for individual risk preferences in the mobility equation. We use discrete choice models to estimate workers' probability of moving, given a set of human capital and firm specific characteristics thought to explain mobility. We test the empirical relation between risk preferences and job mobility using a probit model. The estimation model is specified as follows:

$$left\_firm_{it} = \delta_0 + \delta_1 R_{it} + \delta_2 \boldsymbol{X} + \mu_{it} \quad (4.13)$$

Our dependent variable $left\_firm_{it}$ is bivariate, and we code participants one if they left a firm and zero if they stayed (between the two waves of the survey (2015 -2016)). Our main variable of interest R_{it} captures workers risk aversion. The variable $\boldsymbol{X}$ captures a set of covariates, including individual and job characteristics empirically shown to explain job mobility. These variables include, age, gender, marital status, household size, education, tenure, nature of employment contract, sector of employment, and employment shocks.

The empirical literature shows that risk aversion may affect individuals' occupational and sectorial choices (Bennett *et al.*, 2012a; Falco *et al.*, 2011; Skriabikova *et al.*, 2014).This may raise concerns that certain firm and job characteristics may be 'bad controls' in our model. Unfortunately, our data only captures workers information post labour market entry. We argue that controlling for these characteristics is important, as it provides insights on the empirical relationship between risk aversion and job mobility, conditional on firm and job characteristics. We therefore estimate different specifications of the mobility model: initially, we exclude risk preferences and estimate the basic model, including controls for firm and job characteristics. We then control for risk aversion (R_{it}), and incrementally add controls for firm and job characteristic in subsequent models ($\boldsymbol{X}$).

4.6 EMPIRICAL RESULTS

4.6.1 Risk Preferences and Mobility Patterns

Table 4.2 presents the main findings of estimation equation 4.13. We interpret the results as marginal effects on the probability of experiencing job mobility for each covariate (as specified in the model). Our dependent variable is binary and takes a value of one if a worker has moved from their previous job and zero if they have stayed.

Table 4.2: Effects of risk aversion on employee mobility

Left firm	1	2	3	4	5	6	7
Risk_Ave			-0.050***	-0.048**	-0.037**	-0.047**	-0.035
			(0.019)	(0.019)	(0.018)	(0.023)	(0.036)
Age	-0.005	-0.006		-0.019*	-0.007	0.003	0.003
	(0.010)	(0.008)		(0.011)	(0.012)	(0.017)	(0.017)
Agesqr	0.093	0.094		0.240*	0.127	0.039	0.045
	(0.111)	(0.089)		(0.126)	(0.137)	(0.186)	(0.186)
Male	-0.069	-0.026		-0.092	-0.079	-0.104	-0.100
	(0.049)	(0.038)		(0.062)	(0.061)	(0.081)	(0.081)
Married	-0.092	-0.085			0.009	-0.003	-0.007
	(0.062)	(0.052)			(0.060)	(0.079)	(0.081)
yrs_educ	-0.002	-0.003			-0.002	-0.005	-0.005
	(0.008)	(0.006)			(0.010)	(0.012)	(0.012)
Hhsize	0.013	0.013*			0.006	0.005	0.005
	(0.008)	(0.007)			(0.010)	(0.013)	(0.013)
log_tenure	-0.082***	-0.040**			-0.058**	-0.133***	-0.131***
	(0.021)	(0.017)			(0.026)	(0.036)	(0.036)
Shock	0.117***					0.154***	0.139**
	(0.035)					(0.057)	(0.068)
Informal		-0.139***			-0.136***		
		(0.024)			(0.038)		
permanent						-0.027	-0.029
						(0.066)	(0.066)
Risk_Ave:shock							-0.085
							(0.211)
Num. obs.	485	653	313	313	311	230	230
Log Likelihood	-201.75	-266.57	-135.59	-132.53	-125.50	-96.006	-95.925
Deviance	403.514	533.140	271.182	265.079	251.003	194.011	193.850
AIC	421.514	551.140	275.182	275.079	271.003	216.011	217.850
BIC	459.171	591.474	282.674	293.810	308.400	257.268	262.546

****p < 0.01, **p < 0.05, *p < 0.1*

Source: Author, 2019.

The basic mobility equation, excluding risk measures (column 1 and 2), shows that a worker's household size, tenure, sector of employment, and employment level shocks explains external job mobility. The results show that the main demographic characteristics (age, gender, marital status) except for household size fail to explain mobility. Workers from large sized households are more likely to move from their jobs. Workers with longer tenure are less likely to move compared to those with short tenure. Following the search and match literature, the results imply that these individuals are more likely to have evaluated and concluded that their current job provides the best match quality. As such, quitting a job may mean forfeiting a secure job and employment benefits. In an environment of constrained outside alternatives, this may be costly. On the other hand, firms may be reluctant to fire their long serving workers, mainly because of the costs associated. These could be terminal benefits (which increase with tenure), institutional memory, and accumulated firm specific human capital (training). Interestingly, we find that job mobility is more common in the formal sector, as compared to the informal sector. The results are a reflection of the increasing significance of the

informal sector as a source of employment in the face of a massive contraction of formal manufacturing activities in Zimbabwe.

In the subsequent columns (3 through to 7), we address the main research question by controlling for individuals risk preferences using the computed Arrow-Pratt risk aversion measure. Our result is in line with our theoretical prediction, supporting the proposition that risk averse workers are less likely than risk tolerant workers to experience job mobility. A standard deviation increase in risk aversion is associated with roughly a 5% decrease in the probability of mobility (holding everything else constant). To check if our results are sensitive to different specifications, we add controls for individual and job characteristics in subsequent specifications (column 4 to 7). Interestingly, age and its square become significant in column 4; the weak relationship (an inverted one) however, varnishes as we add controls for other human and job characteristics that typically explain job mobility. In column 5 to 6, we control for tenure, sector of employment, and employment shocks. Our main variable of interest remains statistically significant and returns the hypothesised relationship. To this end, our results find empirical support from recent studies on the effects of risk aversion on job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016; Vardaman *et al*., 2008). Job mobility is inherently risky; it can potentially result in a bad match, loss of earnings and employment benefits and - in the case of Zimbabwe - long-term unemployment.

In Section 2.3, we argued that labour market conditions might moderate the effects of risk aversion on worker's mobility decisions. In particular, it may be more risky to leave a stable job in a firm that is doing well, than it is to leave a sinking ship. We test this hypothesis in column 7, by interacting risk aversion and employment shocks. Our results show that that there are no interaction effects between risk aversion and employment shocks on job mobility; both the interaction term and the risk aversion variable become insignificant. The employment shock variable, however, remains statistically significant. Interestingly, the results return the same direction of relationship, and the coefficient (risk aversion plus interaction term) is almost similar to the one reported in column 3. One explanation could be that the interaction term may have restricted the number of observations between the categories of movers and stayers.

4.6.2 Binary choice fixed effects model on risk preferences and job mobility

Information from the Zimbabwe national budget (2015) shows differences in capacity utilisation by industrial sectors, with the food and beverages sector - for instance - reporting the highest level of capacity utilisation (GoZ, 2015). As part of the robustness checks, we control for the role of unobservable industrial sector characteristics, which may affect worker's mobility decisions. We argue that workers' industrial sector could potentially hide important information that may help us understand the effects of risk aversion on the observed patterns of job mobility. To address this, we estimate industry fixed effects models for the risk subsamples using the bife package in R (Stammann *et a*l., 2016). The survey collects data from seven industrial sub-sectors, and we use the

industrial subsector as the unit for our fixed effects. We present the probit fixed effects model parameters in the appendices (Table C.3). For easy of interpretation, in Table 4.3, we present the model average partial effects computed using *apeff_bife( )*, an inbuilt function of bife package in R.

Table 4.3: Probit Model Average Partial Effects on Risk Preferences and Mobility

Left job (1= yes)	APE
Risk aversion	-0.053**
age	-0.021
agesqr/100	0.307*
male	-0.102*
married	-0.007
yrs_educ	-0.063
educsqr	0.002
hhsize	0.008
tenure	-0.008**
Shock	0.154***

Note: Average partial effects are sometimes referred to as marginal effects (Stammann et al., 2016).

Source: Author, 2019.

The results confirm the main empirical predictions: risk averse workers are significantly (at the 5% level) less likely to move, as compared to their risk tolerant pears. The result is robust to the inclusion of industry fixed effects, indicating that workers' behavioural attributes play an important role in shaping mobility decisions. Interestingly, the fixed effects model reveals that male workers are less likely to move compared to their female peers. The other variables reported as significant, in Table 4.2, also return the same relationship.

4.6.3 Individual and job characteristics as moderators of mobility

So far, we have modelled the empirical relation between risk aversion and job mobility using the base model. However, in addition to the main relationship, it is possible that certain circumstances will alter the strength of the relationship. The effect of risk aversion is likely to be stronger among employees that:

i) Have permanent contracts, compared to those on temporary contracts;
ii) are in formal employment; and
iii) have had on the job training.

To test these hypotheses, we interact risk aversion with dummies on employment contract, sector of employment, and on the job training. Table C.4 presents the probit model average marginal effects of risk aversion, estimated on workers in different employment sectors and on different employment contracts. Our interaction effects are insignificant; the results suggest no evidence of heterogeneity in effect arising from different sectors of employment, employment shocks or different employment contracts. This is also true for interaction terms that control for gender and marital status.

In addition to this, as part of additional robustness checks, we define a candidate proxy of risk attitude based on gamble participation; we group workers who took part in the gamble as risk tolerant and those who abstained as risk averse. We use this proxy variable to estimate job mobility. The variable is insignificant across all specifications. The result is unsurprising and suggests that this is a rather crude measure of individuals risk aversion, and as such, fails to capture individuals risk attitudes.

4.6.4 Risk aversion and nature of mobility

Following the discussion in the conceptual framework, it is important to investigate whether risk attitudes gravitate individuals towards voluntary or involuntary job mobility. Our data set contains subjects' reasons for job changes. To address the question of the nature of mobility, we group the reasons into three main categories: voluntary mobility, involuntary mobility and closed firms. This variable restricts our analysis to individuals working in firms that report job mobility. Doing so guarantees that we are comparing individuals who are likely to have made job mobility decisions whilst in similar work circumstances. We model the job mobility process as a multinomial logit model comprised of four categories: stay (base outcome), voluntary mobility, retrenched, and firm closed.

Table C.5 is a summary table of the multinomial logit estimates for three different specifications. We control for sector of employment, employment shocks and, in the last model, we interact shocks with risk aversion. Our estimation results report a negative relationship between risk aversion and mobility; however, the coefficients are mostly insignificant. There are fewer observations per each category, this potentially undermines the explanatory power of the sample. Future research with large samples can benefit from further exploring for this.

4.7 DISCUSSIONS AND CONCLUDING REMARKS

Traditionally, on-the-job-search and job matching models formed the basis of analysing job mobility (Burdett, 1978; Jovanovic, 1979) and wages constituted the central variable. Over time, studies have taken an interest in identifying other variables (including human capital and job characteristics) that explain job mobility (Hwang *et al*., 1998; Pavlopoulos *et al*., 2014; Sullivan, 2014). However, there are further important sources of job mobility that are not directly observable; and attitudes towards risk is one of them (Argaw *et a*l., 2017; van Huizen & Alessie, 2016; Vardaman e*t a*l., 2008). In this study, we build on the work of van Huizen & Alessie (2016) and address theoretically – and examine empirically – the effects of risk aversion on job mobility. We adopt a model in which risk preferences can potentially affect job mobility decisions through two channels: job search and reservation match. Using experimental data from Zimbabwean manufacturing, we contribute to the literature on the role of risk preferences on job mobility by extending the analysis to a developing country characterised by uncertainty.

Allowing for heterogeneity in economic preferences, we show that risk aversion explains employee mobility. The significant relationship between risk aversion and job mobility is robust to the inclusion of moderators and industrial sector heterogeneity. The results are consistent with earlier findings

and confirm the theoretical predictions of van Huizen & Alessie (2016). The study has important implications on the employment dynamics in an environment characterised by economic uncertainty, in particular how individuals' behaviour influence decision making. These findings are an important basis towards tapping the potential of the MEPLMAZ data. The data are well suited for many potential agendas on the effects of variations in risk preferences on labour market outcomes. One example is the combined effect of risk preferences and personality traits on employment outcomes, related to sectoral selection, earnings, and job mobility. In particular, it may be interesting to see if personality traits moderate the effect of risk preferences on individuals' life outcomes.

One issue that is of concern for our results is reverse casualty that may bias the estimated coefficient on risk aversion. Individuals may change their risk attitudes because of their labour market experiences. This may be particularly true for our survey participants, who were interviewed after entering the labour markets. Some of the workers had experienced job changes before; we therefore fail to capture any possible changes in risk attitudes that could have happened before the survey that could include a reversed casual direction of job changes affecting attitudes towards risk. Previous studies investigating the effects of risk preferences on job mobility, however, find no evidence of such reverse casualty (Argaw *et al.*, 2017). In addition, a new strand of literature examining the stability of risk preferences has not yet produced compelling evidence that shows systematic changes for risk preferences in adulthood (Falk *et al*., 2018).

As an extension to the main objectives of the study, we follow Skriabikova *et al*. (2017) and put to test the hypothesis that risk aversion may affect the effect of job mobility on wage growth. We fail to find evidence to support this in the Zimbabwean manufacturing sample. We however, cannot conclude that risk aversion has no effect on wage growth. Future studies could expand on these findings and use a larger sample to track the wage effects of job changes accounting for individuals risk attitudes.

CHAPTER 5

OUTSTANDING SALARIES: DO TIME PREFERENCES MATTER?

ABSTRACT

This paper empirically examines the effects of time preferences in explaining the incidence of outstanding salaries amongst a sample of Zimbabwean manufacturing workers. We use experimental data drawn from an incentivised choice task to compute workers exponential and hyperbolic discount rates. We control for individuals' discount rates, and estimate probit models on the probability of reporting outstanding wages as a function of time preferences and a set of controls that explain individuals' labour supply. Our results show that firm and individual characteristics explain individuals' outstanding salaries; we find no statistical evidence in support of time preferences. However, despite being insignificant, our measures of patience carry the hypothesised positive coefficient. The results could possibly explain a sample selection artefact; less patient individuals may have left jobs.

5.1 INTRODUCTION

Most of life's important decisions involve outcomes that may be realised at different points in time, forcing economic agents to evaluate between taking gains (and losses) immediately or later. How they decide on this, individually or collectively, has recently been a subject of research in the social sciences. One of the legacies of decades of Zimbabwe's economic mismanagement is a decline in manufacturing activates. In particular, employment levels fell as struggling firms' tried to contain overheads through downsizing, while others closed shop. The 2014 National Labour Force Survey indicates that about 18% of the 227 000 retrenchments between June 2011 and May 2014 were in manufacturing (ZIMSTAT, 2015). A manufacturing sector survey (2015-2016) indicated that a sizeable proportion of workers (40%) had accumulated substantial amounts in outstanding salaries with their employers. How, and if, such intertemporal trade-offs can be explained by workers' time preferences is an open empirical question we wish to address in this study.

Recent literature in economics demonstrates that time preferences are central in many models of economics involving intertemporal choice (Golsteyn *et al.*, 2014; Perez-Arce, 2017). Empirically, time preferences have been studied in relation to individuals' life outcomes related to health (Borghans & Golsteyn, 2006; Golsteyn *et al*., 2014; Khwaja *et al*., 2007; Satti *et al.*, 2013), education (Perez-Arce 2017, Non & Tempelaar 2016), and human capital investment decisions (Cadena & Keys, 2015; Golsteyn *et al*., 2014). Other studies explore the theoretical and empirical relationship between time preferences and individuals' labour supply decisions (Ahn, 2010; Campbell & Wanrooy, 2013; Drago, 2006; van Huizen & Alessie, 2015; van Huizen & Plantenga, 2014). Much of this literature focuses on job search behaviour, earnings, and job mobility. However, accumulating outstanding salaries involves a trade-off between immediate and future consumption. While a number of plausible factors

may explain this (for instance, firm performance, constrained outside options, having another job etc.), we argue that part of this behaviour may reflect individuals' patience levels.

In economics, a discount rate may be defined in relation to the marginal rate of substitution between current and future consumption (Benzion *et al.*, 1989). Essentially, it represents the rate at which one is willing to trade current value for a delayed future certain outcome. The exponential discounting model is the standard model in economics and assumes that time preferences are time-consistent (van Huizen & Plantenga, 2014). To allow for time-inconsistency and present biasedness, hyperbolic discounting models have been proposed as an alternative model (Laibson, 1997). In applied settings, the alternatives models have been theoretically and empirically shown to lead to different predictions, in respect of job search behaviours (DellaVigna & Paserman, 2005; van Huizen & Alessie, 2015; van Huizen & Plantenga, 2014). We extend this line of argument in this study and empirically examine if this is the case in respect of outstanding salaries.

In this study, we investigate the relationship between time preferences and individuals' labour market behaviour. Specifically, we elicit for workers' time preferences from a simple choice task with monetary rewards, and use the measures to investigate how they relate to outstanding wages amongst a sample of Zimbabwean manufacturing sector workers. We compute the patience measures, both the exponential and hyperbolic formulations, to allow for time inconsistences and present biasedness (Doyle, 2013). Our empirical approach involves estimating the basic model - accounting for traditional individual and job characteristics - that influence individuals labour supply decisions, and then controlling for time preferences. We find that job characteristics, in particular tenure, employment shocks, industrial subsector, and wages, explain outstanding wages. Our measures of patience carry the expected signs but enter the regressions insignificantly. The study sheds insights on individuals' labour supply decisions in an environment characterised by a slack labour market. In particular, we identify some of the factors that explain why individuals continue to commit their labour services, even when their employers owe them unpaid wages.

We structure the study as follows: Section 5.2 discusses the empirical studies that examine the effect of time preferences on individuals' labour market outcomes. In Section 5.3, we describe the data and discuss the empirical model used to analyse the relationship between time preferences and outstanding salaries. Section 5.4 presents the results. The final section discusses the empirical findings and concludes.

5.2 EXISTING EMPIRICAL EVIDENCE

As the inclusion of time preferences in analysing individuals' economic outcomes gathered momentum, studies proposed different methods to capture individual time preferences. Some studies construct a patience measure based on behavioural proxies, including smoking, alcohol consumption, owning life insurance (DellaVigna & Paserman, 2005; Drago, 2006), while others focused on questionnaire items (Borghans & Golsteyn, 2006; van Huizen & Plantenga, 2014).

Cadena & Keys (2015) uses a patience measure based on the interviewer's assessment of subjects' time preferences. Economists argue that questionnaire-based measures may be subjective and experimental methods have thus been preferred. Experimentally-elicited measures of time preferences gathered in field settings have been shown to predict important real-world intertemporal choices (Benhabib *et a*l., 2010; Hardisty *et al*., 2013; Kossova *et al*., 2014; Sutter *et al*., 2011). In the experimental setup, there is consensus that hypothetical payoffs may not truly reflect individuals' discount rates, especially when subjects are sensitive to real monetary payoffs.

Studies have taken an interest in examining the factors that explain differences in the distribution of time preferences. A study in Russia by Kossova *et al.* (2014) found that gender, age, income, level of education, marital status, and household characteristics (size and structure) explain time preferences. Klemick & Yesuf (2008) found that wealth variables significantly correlate with time preferences for an Ethiopian sample. The study however, found no evidence linking other socioeconomic and demographic variables to time preferences. Jamison *et a*l. (2012) argue that there are gender differences in time preferences. Empirical results are, however, mixed: some studies find women to be more patient (Bettinger & Slonim, 2007; Castillo *et al*., 2011) and others find evidence that they are less likely to be patient (Golsteyn *et al*., 2014).

Recent empirical evidence has shown that time preferences explain individuals' labour market behaviour and outcomes. This literature can be broadly classified into two; one strand focuses on how time preferences elicited during early stages of life predict future labour outcomes (Cadena & Keys, 2015; Fouarge *et al*., 2014; Golsteyn *et al*., 2014) and the other on the effects of time preferences elicited during working life on employment outcomes (van Huizen & Alessie, 2015; Paserman, 2016). Fouarge et al. (2014) analyse how risk and time preferences explain young individuals' future occupational choices for a sample of recent graduates in the Netherlands. The study found that patient individuals chose occupations with higher earnings growth, as compared to the impatient. Lee & Ohtake (2014) report related results in Japan; because of the tendency to get immediate gratification, the impatient are more likely to select into temporary work.

Golsteyn *et al*. (2014) found that time preferences influence human capital investments and the associated lifetime earnings. In particular, impatient individuals are less likely to accumulate human capital, as compared to their patient peers. They change jobs frequently; however, such job switches do not come with significant salary increments. The study also found that returns to patience - over the long run - are higher, and they differ by gender: males have higher returns to patience, as compared to females. Cadena & Keys (2015), using an America national survey reported related results. Patient individuals are more likely to earn higher earnings compared to the impatient, and the differences in earnings between the two widens with working age.

In respect of post labour market entry analysis, van Huizen & Alessie (2015) examines the effect of time preferences on career investments, focusing on work effort and job mobility, using a Dutch

sample. The study found that patient individuals expend more effort on the job and are more committed. The study also report that on-the-job search intensity increases with patience. Similar results have been reported in the empirical literature for individuals with low discount rates (patient) in respect of job search (Ben Halima & Ben Halima, 2009; van Huizen & Plantenga, 2014). Because of their high search effort, patient individuals are more likely to exit unemployment (van Huizen & Plantenga 2014). However, some studies produce contrasting evidence, reporting a negative relationship between patience and search intensity (Cadena & Keys, 2015; Drago, 2006).

The literature on the link between time preferences and job mobility shows that impatient individuals are more likely to switch jobs, as compared to the patient (Cadena & Keys, 2015; Drago, 2006; van Huizen & Alessie, 2015). The consequences of job mobility differ, depending on individuals' discount rates; for the impatient, job mobility only improves immediate income at the expense of lifetime earnings (Cadena & Keys, 2015; Drago, 2006). The impatient tend to have low reservation wages; they are, however, more likely to stay out of employment for longer periods, as compared to the patient (DellaVigna & Paserman, 2005; Golsteyn *et al*., 2014).

Despite the growing interest in the study of the link between time preferences and labour market outcomes, there is not much literature on developing countries, particularly in Sub-Saharan Africa. The existing literature takes a developed country bias and focus on labour market outcomes related to occupations, earnings and job mobility. The differences in economic structure and labour markets motivates us to look at the Zimbabwean case. In particular, the labour market experience of Zimbabwean workers is unique; significant portions (40%) of them continue to report for work even when their employers owe them outstanding salaries. We know of no study that investigate the potential link between time preferences and outstanding salaries. Existing studies on labour markets investigate labour market outcomes in relatively stable economic environments with functional labour markets. In this study, we focus on post labour market entry, and investigate how time preferences explain one's likelihood of reporting outstanding salaries.

5.3 TIME PREFERENCE DATA

In 2015, SALDRU undertook a sample of Zimbabwean formal and informal manufacturing sector firms and workers. The survey contains modules on individuals' behavioural and psychological attributes that have been shown to explain differences in economic outcomes, including those related to labour markets. The survey randomly assigned subjects to either the risk or time preferences experiment; in this study, we focus on the time preferences subsample. Time preferences describe how individuals make decisions involving trade-offs between immediate and delayed rewards. Subjects in an experiment receive a payoff in accordance with their own decisions. The benefits of incentivised experiments is that they allow for choices reflective of real life situations that can be observed for different individuals (Falk *et al*., 2016). Determining measures of these economic

preferences therefore lays an important foundation for examining their role in explaining economic outcomes, including those related to labour markets.

Of interest to us now is the 2015 wave of the survey, which contains a novel set of questions that constitute the time preference experiment. Using a computer generated algorithm, the survey randomly assigned 799 participants to different time choices valued between US$2 and US$7. The time preference task involved individuals choosing between taking an immediate but lower fixed amount (US$2) or a delayed but higher amount. The survey uses the following question to infer individual time preferences:

> *As a token for participating, we would like to give you some airtime credit. Either we can transfer US$2 to your phone tomorrow or transfer US$2 + x to your phone next week, where x is some positive number (US$0 to US$5). Which one would you like? How much money will make you wait until next week? What amount would make you rather take the US$2 now?*

From the simple experiments, we gather information on individuals' time choices and the associated amounts that would rather make them reverse their initial choice. We examine how time choices vary across subjects by summarising the raw data in Table 5.1. Disaggregating between participants that took the immediate and delayed option by the time option offered, a majority of participants chose the delayed option (62.7%), foregoing the lower but immediate payment. The proportion of individuals choosing the delayed option increased with increases in stakes. This suggests that with lower stakes, the opportunity cost of waiting is relatively low; however, it increases with higher amounts.

Table 5.1: Time choice

Time Amount US$	Number of workers	Now	Wait	*p*-value
$2 now or $2 in a week	18	9(50%)	9 (50%)	1.000
$2 now or $3 in a week	88	54 (61.4%)	34(38.6%)	0.033
$2 now or $4 in a week	202	80 (39.6%)	122 (60.4%)	0.003
$2 now or $5 in a week	196	69 (35.2%)	127 (64.8%)	0.000
$2 now or $6 in a week	192	60 (31.3%)	132 (68.8%)	0.000
$2 now or $7 in a week	101	26 (25.7%)	75 (74.3%)	0.000
Total	**799**	**298 (37.3%)**	**501 (62.7%)**	

NB: There was a coding error that assigned workers to the $2 experiment, this was however fixed.

Source: Author, 2019.

Figure 5.1 gives a visual representation of the data in Table 5.1, but further expresses the proportions of individuals' time choices by occupational sector. The data suggests differences in individuals' time choices across different occupational sectors, as shown in plot (d). Formal employees 647 (66.3%) and self-employed 91 (55.7%) had higher proportions of those that chose to wait compared to the informally employed 61 (41.7%). A Chi-square test for the mean differences between those that took the immediate and delayed option by occupational sector show significant differences between these

categories (X-squared = 21.927, df = 2, p-value = 0.000). This may suggest that time preferences differ by one's occupational sector, and could possibly explain any sectoral differences in individuals labour market outcomes including outstanding wages.

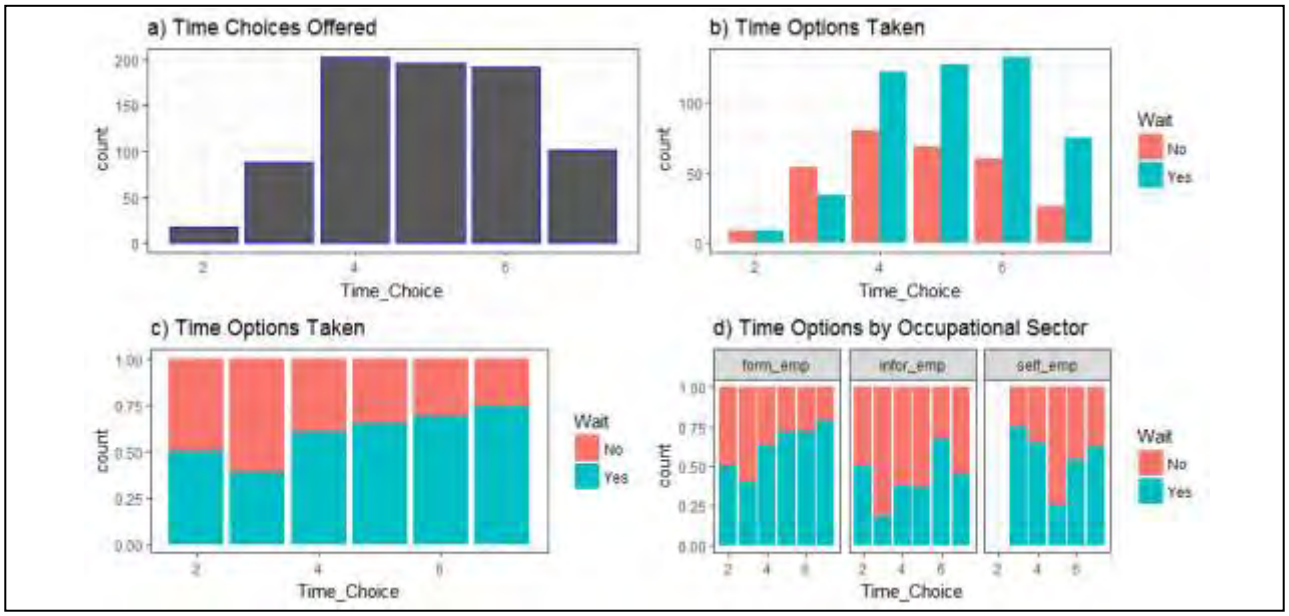


Figure 5.1: Time choice plots

Source: Author, 2019.

Determination of workers' time preferences requires information on individuals' present and future values, those that make them indifferent between the immediate option and the delayed option. The experimental set up directly elicits for these. In Figure 5.2, we summarise individuals' future (present) values, classified by their time choice; the straight lines represent the amounts accepted by subjects in the time preference experiment. Panel (a) focuses on the subjects who chose to wait; the red line summarises the average amount of money that would tempt subjects to forfeit the higher but delayed payouts (future value) for the immediate option (present value). Panel (b), on the other hand, focuses on individuals who chose the immediate option (US$2), over the various options represented by the red line (present value). The blue line represents the average amount of money that would tempt subjects to forego the immediate option (US$2) and wait for a week; these subjects rejected the initial offer (red line).

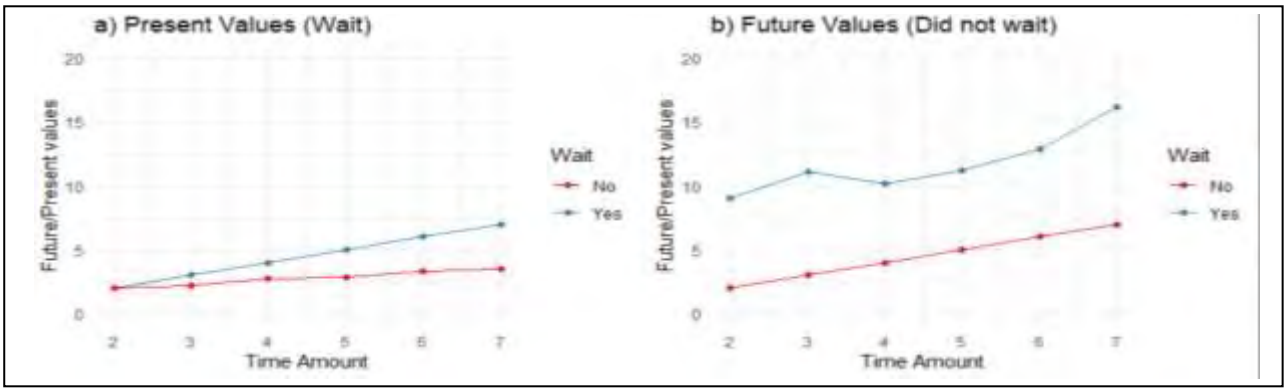


Figure 5.2: Future and present values for individuals participating in the time preference task

Source: Author, 2019.

In both plots, the higher line represents the future value (i.e. value acceptable after a week) while the lower line captures individuals present values (amount acceptable now). More than doubling the amount offered would (on average) tempt subjects who chose the immediate option to wait for a week, while amount less than US$3.50 would tempt individuals offered amounts between US$4 to $7 to take the immediate option.

5.3.1 Characteristics of individuals' time choices

To check for factors that may explain individuals time choices, we estimate a probit model with a binary dependent variable "wait", which takes a value of one if subject waits and zero otherwise. Table D.1 provides the probit model marginal effects on individual time choices as a function of a number of controls, including the time amount offered. The amount offered is positively related with waiting. In addition, married workers are less likely to wait, as compared to those who are single. The more educated one is, the higher the probability of them choosing the option to wait. Age positively correlates with waiting (though weakly); we further report a negative relationship between one's earnings and waiting. Generally, informal sector participants are less likely to wait when compared to their formal sector peers. We found no interaction effects between amount offered and gender on individuals' time choices.

5.3.2 Measuring time preferences

The central variable in this study is an indicator of workers' time preferences. In measuring time preferences, we make a crucial assumption that subjects take the experiment in isolation of their constraints or circumstances outside the experiment [20]. For instance, in deciding between immediate and later rewards, we assume that participants are not influenced by their credit constraints or interest rates outside the laboratory (Falk *et al.*, 2016). In this study, we infer workers discount rates from the reported present and future values, which make individuals indifferent between accepting the amount immediately and delaying.

The standard model of determining time preferences in economics is the exponential discount rate; however, it hinges on the assumption of time consistency. Empirical work has shown, however, that individuals are time inconsistent in making intertemporal decisions, which has led to the development of the hyperbolic discount rate. To test if exponential or hyperbolic discount rates best describe the

[20] Individuals circumstances may have shaped subjects' choices in the experiment, for instance trust issues may have inclined individuals to take an immediate payout even though they would have ideally preferred a higher delayed amount. An individual with a pressing need to make a say to a client or a supplier (especially informal sector workers) may be induced into taking an instantaneous US$2 worth of airtime (which could create more business) than waiting for a week to get US$4. In as much as we argue that the payouts represent significant amounts, this may not be true for those in the higher earnings bracket. This may also put to question the incentive compatibility of our experiment.

respondents' time preferences, we adopt both measures in determining individuals' discount rates. To infer discount rates from intertemporal decisions, we follow the formulations as summarised by Doyle (2013).

The exponential discount rate is given by:

$$F = Pe^{rT} \quad (5.1)$$

Rearranging this gives:

$$r = \frac{1}{T} ln\left(\frac{F}{P}\right) \quad (5.2)$$

The hyperbolic discount rate is defined by:

$$h = \left(\frac{F}{P} - 1\right)/T \quad (5.3)$$

where $F\ is$ the future value, P is the present value and T the time delay (in our sample, the time delay was 7 days). The computed mean exponential discount rate is 0.09 (s.d. = 0.13) and that for the hyperbolic discount rate is 0.517 (s.d. = 3.016).

5.3.3 Characteristics of individuals' time preferences

At this stage, we take interest in exploring the distribution of individuals' time preferences. We estimate first stage regressions on the relationship between the computed patience measures and a set of covariates believed to correlate with individuals' time preferences (Appendix 5.3 and 5.4). Table D.2 reports the OLS regression on the relationship between the exponential discount rates and a set of demographic characteristics (age, gender marital status, education, location, and sector of employment). Estimation results show that age, ethnicity, geographical location, and sector of employment, explain differences in time preferences (exponential discount rates). The other covariates insignificantly correlate with the computed exponential discount rates. As with the exponential discount rates, we estimate an OLS regression for the hyperbolic discount rates. Table D.3 summaries the regression results. All the explanatory variables enter the equation insignificantly, and this is the case for different specifications of the equation.

5.3.4 Outstanding Salaries

Our data exposes us to one feature peculiar to the Zimbabwean workers: a significant proportion of the worker sample (40.8%) report outstanding pay. We zoom into the data and examine how outstanding salaries are distributed across the sample. Figure 5.5 gives a snap shot of the sampled individuals in manufacturing jobs who report outstanding salaries in the second wave of the survey, disaggregated by firm size and median wage. Outstanding pay is highest amongst smaller firms (those with 5 to 19 employees), where almost two-thirds of employees are owed wages. Interestingly, outstanding wages are more likely for those workers who earned below the median wage in 2015.

Overall, and in the two smaller firm size groups (5-19 and 20-99 employees), higher paid workers at the start of the survey were at least 10 percentage points less likely to be owed wages in 2016.

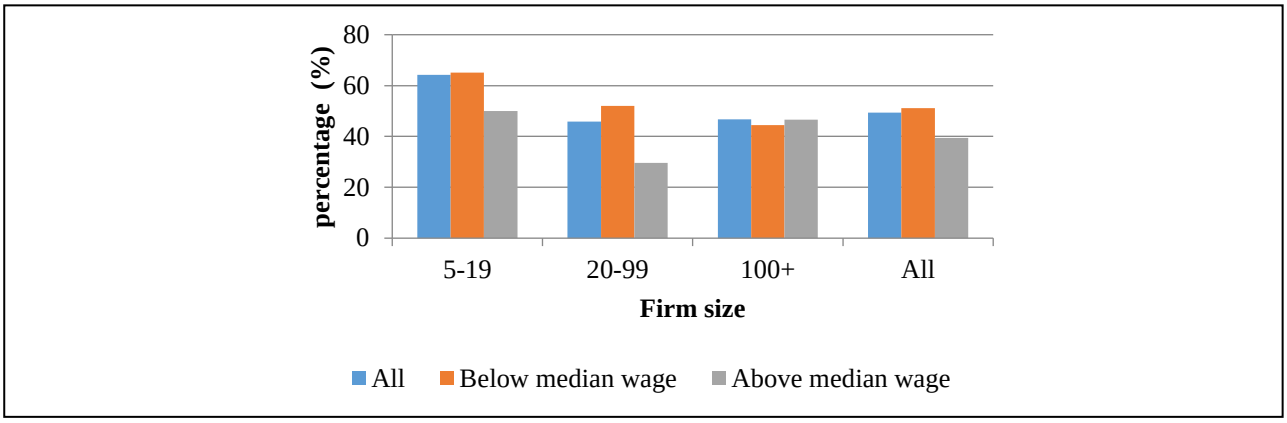


Figure 5.3: Proportion of workers with outstanding pay in 2016, by firm size and wage level in 2015.

Source: Author, 2019.

A number of plausible reasons to explain this phenomenon can be inferred from the survey. Firms cannot afford the retrenchment cost: the Zimbabwean labour regulation stipulates that fired or retrenched workers should be paid packages in proportion to the length of time they have worked for the firm. Workers thus have an incentive not to leave the job voluntarily, since they would lose this claim. The data shows this: in the sample, average tenure is approximately 12 years, but those with outstanding pay have approximately two years longer tenure than those without. A second related reason is that workers may simply just be waiting for the firm to do better with the hope that they will be paid when this happens.

Thirdly, it may be that workers who are prepared to accept not being paid fully have different risk or time preference profiles. We examine the distribution of outstanding salaries by individuals' time choices in the time preferences experiment. Those with outstanding pay were about 8 percentage points more likely to wait for delayed higher amounts, than those with no outstanding pay:

Table 5.2: Time choices of workers (proportions)

	Wait	***p*-value**	**Other jobs**	***p*-value**	**Remittances**	***p*-value**
No outstanding pay	60.7%	0.113	68.9%	0.668	86.0%	1
Outstanding pay	68.5%		71.8%		85.8%	

NB: p-values from chi-square tests on equality of means

Source: Author, 2019.

The fourth potential reason why underpaid workers do not leave is that outside options are limited. One potential outside option is the informal sector, and this may not be an attractive option, given the associated income risk. A fifth reason is that they may be engaging in other outside activities, which provide an additional revenue stream. About a quarter of the sample report having an external activity, although there is negligible difference in proportions (about 3%) between those with outstanding pay and those without.

5.3.5 Estimating Outstanding Salaries

Our analysis draws from data reported in the second wave of the survey, where a significant portion of the sample reported outstanding salaries. To examine if there is heterogeneity between those that report outstanding wages and those that do not, we use discrete choice models. In particular, we rely on probit models to estimate a worker's probability of outstanding salary, given a set of individual and firm specific characteristics (including time preferences). Essentially, we test for the hypothesis that time preferences explain employee mobility between the two waves of the survey. We specify the estimation model as follows:

$$OutstandingW_{it} = \delta_0 + \delta_1 TP_{it} + \delta_2 X_{it} + \mu_{it} \quad (5.4)$$

The dependent variable $Outstanding\ W_{it}$ is a dummy variable taking a value of one if employees report outstanding salaries in 2016 and zero if they do not. Our main variable of interest (TP_{it}) captures individuals' time preferences (exponential and hyperbolic discount rates). X_{it} is a set of covariates including age, marital status, years of education, household size, tenure, firm level employment shocks, and sector of employment. We estimate different specifications of the outstanding salaries model; initially, we excluded measures of time preferences and focused on the traditional economic variables captured by X_{it}. In subsequent models, we control for individuals time preferences using both the exponential and hyperbolic discount rates.

5.4 EMPIRICAL RESULTS

The goal of this section is to examine the empirical relationship between time preferences and outstanding salaries for a sample of Zimbabwean manufacturing sector workers. We estimate a probit model on the probability of outstanding wages as a function of individual and firm characteristics, including time preferences (as specified in Equation 5.4). Our dependent variable was measured in 2016, and we used covariates reported in 2015. Our empirical approach involves estimating the basic model using the whole sample, and controlling for time preferences using the time preferences subsample. We use both the exponential and hyperbolic discount rates to estimate the effects of individuals time preferences on mobility patterns. Doing so allows us to empirically test whether the effects of time preferences on outstanding salaries differ, depending on whether one discounts exponentially or hyperbolically.

5.4.1 Time preferences and outstanding salaries

To assess the relation between time preferences and outstanding pay, we estimate a probit model with a dummy as a dependent variable, indicating whether a worker reports outstanding wages or not. The basic model controls for demographic characteristics (age, age squared, marital status, size of household, years of education), employment shocks, extra jobs, firm size and the industrial subsector. We further control for time preference measures, both exponential and hyperbolic discount rates in our model. Table 5.3 summaries the estimated probit model marginal effects with

and without controls for time preferences. It should be noted that employment shocks are only recorded for formal manufacturing firms, and there are some missing observations, this reduces the number of observations across different specifications.

Table 5.3: Average marginal effects on time preferences and outstanding salaries

	Basic model		Exponential model		Hyperbolic model		Time choice model	
Owed wages	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Expon			-0.017	-0.047				
			(0.182)	(0.292)				
shock:Expon				0.185				
				(0.426)				
Hyper					-0.007	-0.020		
					(0.008)	(0.038)		
shock:Hyper						0.021		
						(0.039)		
Shock		0.161***		0.159**		0.171***		0.173***
		(0.037)		(0.068)		(0.056)		(0.055)
Wait							0.043	0.164
							(0.052)	(0.220)
Time_amount								0.041
								(0.038)
Wait:Time_amount								-0.034
								(0.047)
Age	-0.003	-0.012	0.027	0.028	0.028	0.027	0.026	0.025
	(0.011)	(0.013)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)
Agesqr	0.071	0.179	-0.249	-0.240	-0.258	-0.235	-0.235	-0.209
	(0.126)	(0.142)	(0.221)	(0.238)	(0.221)	(0.238)	(0.220)	(0.238)
Male	0.082*	0.043	0.061	0.018	0.060	0.018	0.067	-0.002
	(0.044)	(0.051)	(0.068)	(0.076)	(0.068)	(0.076)	(0.067)	(0.077)
Married	0.037	-0.012	-0.049	-0.095	-0.044	-0.091	-0.030	-0.054
	(0.055)	(0.064)	(0.085)	(0.102)	(0.085)	(0.102)	(0.084)	(0.101)
log_wage	-0.125***	-0.117***	-0.137***	-0.137***	-0.135***	-0.134***	-0.144***	-0.143***
	(0.030)	(0.033)	(0.044)	(0.047)	(0.044)	(0.047)	(0.043)	(0.047)
yrs_educ	0.020**	0.071	-0.008	0.005	-0.007	0.005	-0.009	0.009
	(0.009)	(0.048)	(0.054)	(0.014)	(0.055)	(0.014)	(0.054)	(0.013)
Educsqr		-0.002	0.001		0.001		0.001	
		(0.002)	(0.002)		(0.002)		(0.002)	
Hhsize	-0.000	0.005	0.002	0.017	0.003	0.017	0.004	0.019
	(0.009)	(0.010)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)
Informal	-0.003		0.024		0.024		0.034	
	(0.091)		(0.151)		(0.151)		(0.152)	
log_tenure	0.063***	0.061**	0.035		0.029		0.030	
	(0.024)	(0.027)	(0.036)		(0.036)		(0.036)	
Num. obs.	899	735	415	338	416	338	425	342
Log Likelihood	-585.581	-467.933	-270.316	-212.771	-270.923	-212.441	-276.795	-214.955
Deviance	1171.163	937.865	540.633	427.541	541.846	426.882	553.590	431.910
AIC	1191.163	959.865	564.633	449.541	565.846	448.882	577.590	455.910
BIC	1239.176	1015.064	612.972	495.418	614.214	494.758	626.215	505.763

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: The dependent variable is a binary indicator that equals one if a respondent reports outstanding wages and zero if they have no outstanding salaries. Columns (1) and (2) present estimates for the basic model (without controls for time preference) and this analysis uses the full sample of the survey. Columns (3) to (6)

control for our measures of time preferences (both the exponential and hyperbolic discount rates), and in last columns we use a candidate proxy for patience (wait) based on workers' time choices in the experiment.

Source: Author, 2019.

In column 1, we estimate the basic model, controlling for individual characteristics thought to explain outstanding salaries. Our results show that tenure, gender, and wages explain outstanding salaries. Male workers are more likely than their female peers to report outstanding salaries; this relationship, however, turns insignificant in subsequent specifications. Long-serving employees are more likely to report outstanding salaries, as compared to their peers with a short tenure. Firms that cannot afford the retrenchment costs postpone the immediate payment of such costs by accruing outstanding wages, in the hope of improved firm performance in the future. Zimbabwean labour regulations stipulates that fired or retrenched workers should be paid packages proportionate to their tenure with a firm. Because workers are aware of the state of their firms - their abilities and the limited outside opportunities - they would rather accumulate outstanding salaries with their employer than quit. The results show that this is more likely for individuals with a longer tenure, who also happen to have a bigger claim in terms of terminal benefits. Individuals who earn more are less likely to report outstanding salaries. This could potentially reflect the fact that these workers are employed in well performing firms, which can afford to pay salaries in full. In column 2, we add controls for firm employment shocks. Firm employment shocks enter the regression significantly and positively explain outstanding wages. Firms that witnessed a drop in employment levels are - on average - 16% more likely to owe employees outstanding salaries than firms that did not experience employment shocks.

In column 3, we address the central question of this study and control for time preferences in our model. We begin by controlling for individuals' exponential discount rates in the main model to test whether time preferences explain outstanding wages. The results are statistically insignificant, but we report the hypothesised negative association between time preferences and outstanding wages. The results suggests that patient individuals are more likely than their impatient peers to be owed. Interestingly, tenure becomes insignificant, which may signal possible correlations between discounts rates and tenure. In column 4, we include employment shocks and an interaction term between shocks and time preferences (but drop tenure). Wages and employment shocks return the same relationship as in the basic model and are significant. The interaction terms between employment shocks and exponential discount rates is insignificant, suggesting that there is no additional effect of time preference on outstanding salaries through employment shocks. In both specifications, our measures of patience (exponential discount rates) remain insignificant, but return the hypothesised direction of association.

In columns 5 and 6, we replace exponential discount rates with hyperbolic discount rates in our estimation model. Doing so allows us to test if the empirical results differ for hyperbolic and exponential discounters. We largely report results that are comparable to the ones reported for

models that control for exponential discount rates. The measure of patience represented by hyperbolic discount rates negatively relates to outstanding wages; however, it is insignificant. We further extend our analysis by specifying a candidate proxy for patience - defined as a dummy variable - indicating whether one took the immediate or delayed option in the experiment. Columns 7 and 8 controls for this variable in place of the computed measures of time preferences. Further, in column 8, we add an interaction term between waiting and the amount offered in the experiment. The results suggest that individuals who choice to wait in the experiment are more likely than their peers who chose the immediate payment to report outstanding salaries. This finding, though insignificant, is in line with the hypothesis that we test in this chapter: patience is associated with outstanding salaries.

In Table D.4, we extend the analysis and examine if firm and industrial subsector characteristics may help explain outstanding salaries. We do this by adding controls for firm size (four categories: micro, small, medium, and large), industrial subsector (seven categories: food and beverages, textiles, leather, wood products, chemicals, rubber, and plastics, as well as the metals and machinery subsectors) and dummy variables capturing whether workers receive remittances and have an additional job. To test for the effect of the industrial sector, we use the food and beverages industry as the base industrial sector. Our results show that employees in the chemicals and metals machinery subsectors are more likely - on average - to experience outstanding wages, as compared to those in the food and beverages industries. We found no statistical evidence, however, between the food and beverages subsector and the other three industrial subsectors. Using micro firms as the base, we find no statistical evidence of the relationship between firm size variables and outstanding salaries. Our dummy variables for remittances and extra jobs are insignificantly associated with outstanding wages.

5.5 DISCUSSION AND CONCLUSIONS

A particularly striking characteristics of Zimbabwean manufacturing sector workers is reporting for work while being owed salaries. How and why workers are seemingly able to sustain this for extended durations is a question that merits empirical examination. This phenomena, which seems pervasive in Zimbabwean manufacturing, has however evaded the attention of economist in the empirical literature. Perhaps justifiably so as outstanding salaries are not prevalent in most economies. In this paper, we hypothesise that individuals' behaviours – in particular their patience levels, may help to explain this. To address this question, we exploit the matched employer-employee Zimbabwean survey data (2015-2016), which contains detailed firm and worker information including time preferences. The 2015 wave of the survey contains experimental data which we use to compute workers' exponential and hyperbolic discount rates, and empirically examine if they explain outstanding salaries in 2016. Our empirical approach involves estimating

binary choice models, initially focusing on job and individual characteristics, hypothesised to explain outstanding salaries and then controlling for time preferences.

Our main findings suggest that patience (measured by both exponential and hyperbolic discount rates) is positively associated with outstanding salaries. This is also true for the wait dummy (a proxy for patience); however, the variables enter insignificantly in the regressions. This could potentially reflect a sample selection artefact: the sample size and also the fact that the impatient may have left their jobs already. We find that job characteristics (mainly wages, tenure, industrial subsector, and firm employment shock) are important in explaining outstanding wages in Zimbabwe. Based on these findings, the results shows that variables that capture firm performance explain the probability of outstanding wages. The study sheds light on the labour supply decisions of developing country workers in an environment characterised by uncertainty.

CHAPTER 6

PERSONALITY TRAITS, RISK AND TIME PREFERENCES: LABOUR MARKET ANALYSIS IN ZIMBABWE

ABSTRACT

Using novel Zimbabwean firm level data, we contribute to the nascent and rapidly growing empirical evidence on the significance of personality traits, risk, and time preferences on employment outcomes. Intuitively, since these behavioural measures are different, accounting for them should enrich our understanding of how individuals' life outcomes differ. We estimate their joint effects on sectoral occupation, earnings and job mobility in a developing country characterised by economic uncertainty. Our results show that over and above personality traits, risk and time preferences explain an individual's sector of employment, earnings, and job mobility. We find empirical support for the simultaneous inclusion of different behavioural measures in models examining individuals' economic outcomes.

Keywords: Risk preferences, Time preferences, Big Five, Earnings, Job Mobility.

6.1 INTRODUCTION

The economic fortunes of most individuals in developing countries is largely dependent on their labour market experiences: that is, by their occupations, which ultimately define paths to wages. Economists have thus taken a natural interest in building theoretical models examining the sources of differences in individuals' employment outcomes. At the heart of the analysis of labour markets are search and match theories (Jovanovic, 1979; Mortensen, 2011; Mortensen & Pissarides, 1994). While a vast amount of literature examines the extent to which human capital variables explain differences in labour market outcomes, a more recent effort has found that behavioural and psychological attributes can explain some of these differences even within a given range of human capital variables. Research on personality traits, risk, and time preferences - in particular - has recently been a blossoming field in economics.

To date, most studies on labour market outcomes focused on the effects of personality traits, risk and time preferences in isolation (Almlund *et al.*, 2011; Borghans *et al.*, 2008b; Campos *et al.*, 2016; Heckman & Kautz, 2012; Nyhus & Pons, 2012; Reuben *et al.*, in press; Sharma & Tarp, 2018). These concepts, while related in the sense that they capture unobservable heterogeneity in human behaviour, are clearly distinct. One might presume that since they measure different aspects of human behaviour, simultaneously accounting for them in economic models may particularly help explain part of the unexplained residual differences. Yet, despite this, there is limited evidence that provides a unified analysis on their combined effects on individuals' life outcomes (Caliendo *et al*., 2014; Sharma & Tarp, 2018). This could potentially reflect the lack of data sets that capture both

sets of behavioural and psychological attributes. In this study, we combine personality traits and experimentally elicited measures of risk and time preferences, and empirically examine individual employment outcomes in Zimbabwean manufacturing sector.

Our analysis follows from our previous findings that established that personality traits explain individual sectoral occupation, earning, and job mobility patterns. We replicate these models but extend the analysis by accounting for individual heterogeneity in risk and time preferences. Our estimates of sectoral occupation show evidence of significant relationships between risk and time preferences within workers' occupational sector. We find that more risk averse individuals - and those who are impatient - are more likely to be in both forms of informal employment relative to formal sector employment; this relationship is, however, only significant in respect of exponential discount rates. In analysing earnings, we find that personality traits and hyperbolic discount rates (excepting risk aversion) significantly explain manufacturing sector earnings. The results suggest that short-run impatience explains higher earnings, and this relationship is robust to inclusion of personality trait variables. Estimates of job mobility show significant associations between risk and time preferences and job turnover. Risk averse workers are less likely to move, as compared to their risk-loving peers; the impatient - as captured by exponential discount rates - are less likely to move. Our findings underscore the need to account for both sets of behavioural measures in models that estimate individual economic outcomes.

This study is an important first step that provides an empirical basis for simultaneously accounting for heterogeneity in behavioural and psychological attributes in economic outcomes. As more studies examine the effects of behavioural attributes on life outcomes, there is a need to develop instruments capable of simultaneously capturing these attributes over extended periods. We structure the remaining part of the study as follows: in the next section, we provide a brief description of our data. Section 6.3 summarises the estimation results on the effects of personality traits, risk and time preferences on employment outcomes. We conclude the Chapter in section 6.4.

6.2 DATA

Our data comes from the MEPLMAZ survey (2015-2016), a nationally representative panel study of more than 1 600 manufacturing sector workers. The 2015 wave contains personality trait data, as well as incentivised experiments that capture individuals' risk and time preferences. In Chapter 2, we detail the factor analytical strategy used to extract five factors: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism, which are the broad dimensions defining personality traits (John & Srivastava, 1999b). In Chapter 4 and 5, we compute measures of risk and time preferences. The current Chapter uses the measures of personality traits, as well as risk and time preference, and jointly estimate labour market outcomes models of occupational sector, earnings, and job mobility. In addition to the behavioural and psychological measures, the survey gathers individual and firm specific data, typically collected in labour market surveys. This rich data

set enables us to investigate worker's static and dynamic labour market experiences in an environment characterised by economic uncertainty. Descriptive statistics of the data is in Table E.1; we do this for the full sample and further disaggregate by subsample (risk and time preference).

6.3 MAIN ESTIMATION RESULTS

To assess the joint effects of behavioural and psychological attributes, we control for personality traits as well as risk and time preferences in models of occupational selection, earnings, and job mobility. The analysis in the previous Chapters provide empirical evidence showing that risk and time preferences influence individuals' economic behaviour and choices. This study extends the analysis in Chapter 3 by accounting for heterogeneity in risk and time preferences in the estimated labour market models.

6.3.1 Occupational Selection

The analysis in Chapter 3 confirms the importance of the Big Five personality traits in explaining occupational choices in the labour markets. In this section, we extend the analysis by controlling for heterogeneity in risk and time preferences in the multinomial logit model of occupational selection.

Our selection model has three occupational categories: employees can select into formal employment, self-employment, or informal employment. The estimated multinomial logit models marginal effects with formal employment as the base category are in Table E.2. Figure 6.1 plots the marginal effects for our main variables of interest, extracted from the main regression results. In interpreting these results, we do not consider the relationship as causal, but rather correlations. The data was collected post labour market entry, after workers had selected into occupations.

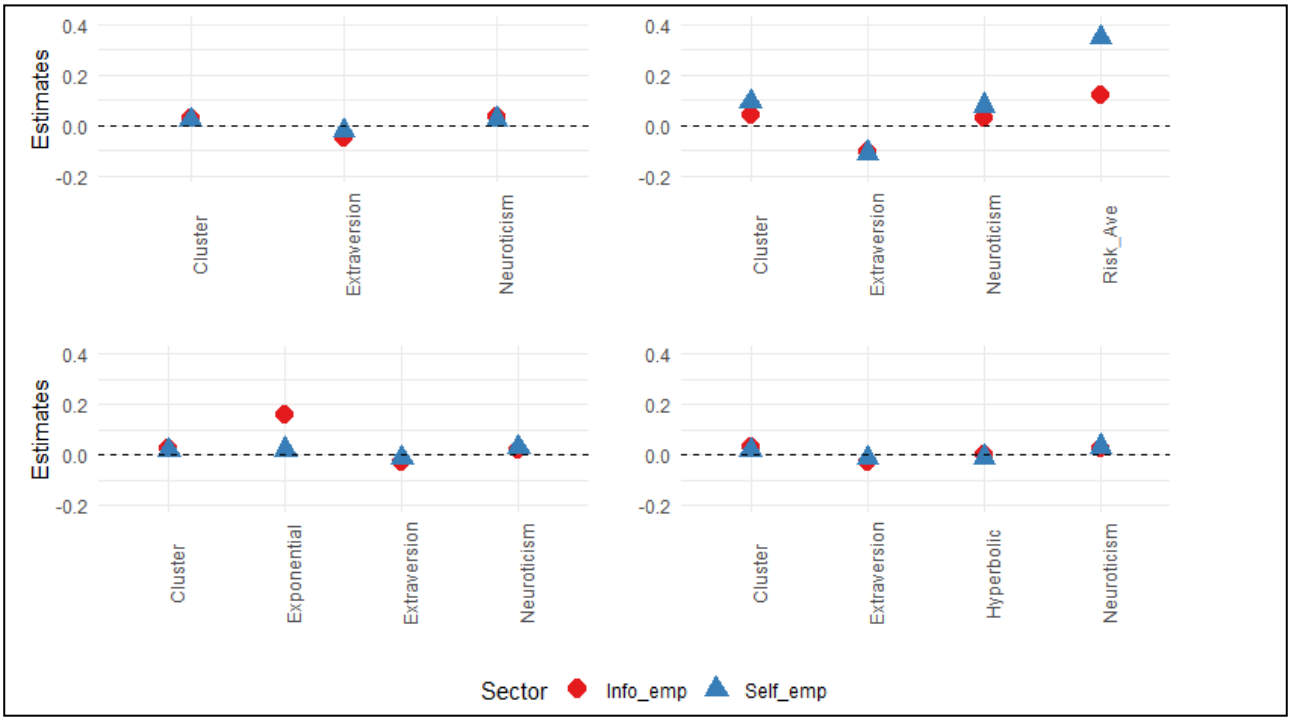


Figure 6.1: Multinomial logit marginal effects of selection into occupational sector

Source: Author, 2019.

The upper left plot replicates the analysis in Chapter 3, and accounts for personality traits in the sectoral occupation model; subsequent plots control for risk and time preference measures. Across different model specifications, we find that highly extraverted individuals are less likely to select into informal sector activities relative to formal employment; on the other hand, highly Neurotic individuals are more likely to be in informal sector employment (both self-employment and informal employment) relative to the formal employment. Individuals who score high in Openness to Experience, Conscientiousness and Agreeableness - as captured by the cluster variable - are more likely to be involved in informal sector activities.

The top right panel delves into the objectives of this study and controls for risk aversion; this restricts our analysis to the risk subsample (N = 860). Our results indicate that risk averse individuals are less likely to select into formal sector jobs; they are more likely to be involved in informal sector activities (self-employment and informal employment). This relationship is robust to the inclusion of individuals' characteristics and personality trait variables that largely return their previous association. Despite, the high income risk associated with the informal sector (Bennett *et al.*, 2012b; Falco, 2014), the results suggest that risk tolerant individuals are more likely to select into the formal sector relative to the informal sector. The results conflict with findings in the empirical literature which reports that risk tolerant individuals are more likely to select into self-employment (Dohmen *et al*., 2011a; Falco, 2014) and occupations with high earnings risks (Bonin *et al*., 2007). Given the different contexts and environments in which these studies were conducted, this could potentially be explained by the effect of risk aversion on job search. Job search comes at a cost, and search activities have an uncertain outcome. The returns of investment in job search may be low in an environment like Zimbabwe, where formal manufacturing activities have been shrinking over the years. Risk averse individuals may, thus, end up in the informal sector, where entry is relatively free and search costs are lower (compared to the formal sector).

The bottom panels provide marginal effects controlling for time preferences, using the computed exponential and hyperbolic discount rates. Our estimates suggest that impatient individuals are more likely to be in informal sector activities, relative to formal employmen; the relationship, though positive, is insignificant in respect of self-employment. Securing a formal job requires investments in job search (van Huizen & Plantenga, 2014), and in a 'slack' labour market like Zimbabwe a successful search may only come after extended periods of queuing. Impatient individuals may not be willing to wait for the arrival of formal jobs and opt for the relatively free entry informal sector. The findings, however, do not provide support for the hyperbolic discount rates. Overall, our models of occupation suggest that assuming homogenous economic preferences potentially miss important unobservable factors that influence individuals' choice of occupational path in labour markets. This may in turn, have important implications in determining individuals' success in the labour market, as economic preferences potentially influence earnings indirectly through occupation.

6.3.2 Mincer earnings equation

In Chapter 2, estimates of the earnings equation showed that personality traits explain differences in earnings. In this section, we follow recent literature documenting the significance of risk and time preferences in explaining labour market earnings (Argaw *et al*., 2017; Dohmen *et al*., 2011a; Ekelund *et al.*, 2005) and extend the analysis to the Zimbabwean sample. Essentially, we control for risk and time preferences in the earnings equation. Table E.3 summarises the estimation results of the augmented Mincer earnings equation. Figure 6.2, depicts regression coefficients for the main variables of interest, summarised for different specifications of the earnings equations.

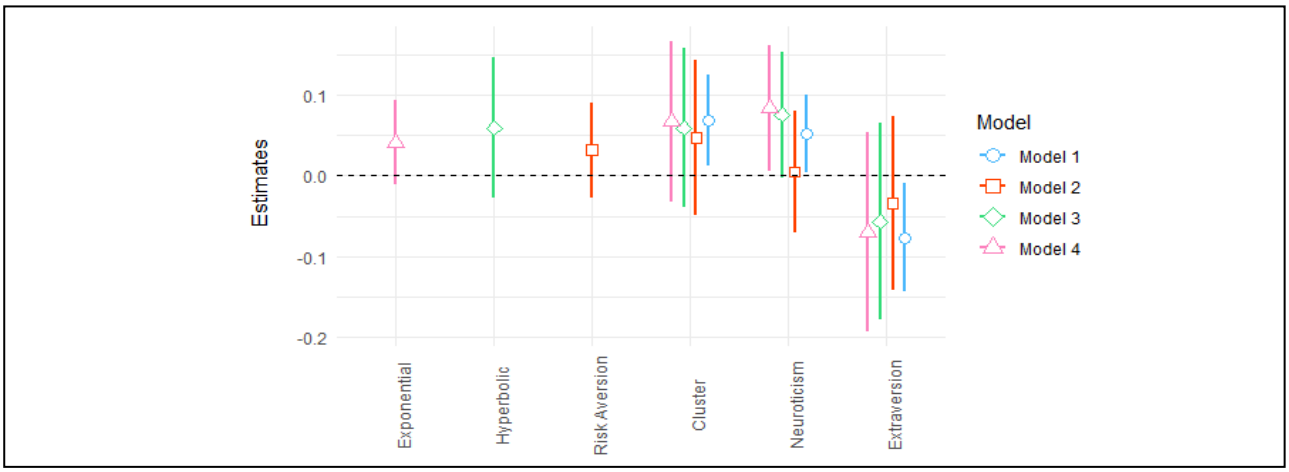


Figure 6.2: Mincer Earnings Equation: Personality traits, risk and time preferences.

Source: Author, 2019.

The blue line summarises the earnings equation accounting for personality traits, the red line summarises regression coefficients accounting for risk aversion, and the green and pink lines reflect models accounting for hyperbolic and exponential discount rates respectively. Because we have noted that three of the five personality trait variables are highly correlated, we prefer the principal component that captures these three variable clusters in our analysis. Across different specifications of the model, we report a wage penalty for individuals who score high in extraversion and a wage premium for workers who jointly score high in openness to experience, conscientiousness and agreeableness (as captured by the Cluster). Surprisingly neuroticism positively correlates with earnings; a finding that is at odds with what is largely reported in literature. This result possibly arises from the way the construct is captured. The factors we extract partially capture the facets of each of the Big Five personality factors, this is a potential challenge posed by reduced item instruments.

In order for us to address the central question of the study, we relax the assumption of homogenous risk and time preferences. Our estimates controlling for risk aversion show a positive but insignificant relationship between our measure of risk aversion and workers' earnings. We retain the same results even after excluding personality traits variable (not shown in the table). The empirical literature reports a wage premium for individuals who are risk loving (Ahn, 2010; Bonin *et al*., 2007; Le *et al*., 2014). Our results find no support for the effects of risk aversion on earnings. This could potentially

be a sample size artefact. Earnings estimates accounting for time preferences find evidence of a wage premium to impatience, but only for workers' hyperbolic discount rate. The results suggest that our measure of short-run patience explains earnings. These findings, however, are at odds with what is mainly reported in the literature, where impatience is usually punished for (Cadena & Keys, 2015). Patient workers are likely to experience wage growth through promotions; on the other hand, impatient individuals may benefit from job mobility linked wage growth (Drago, 2006). The latter may plausibly explain the positive association between impatience and earnings.

6.3.3 Job Mobility

Following evidence from previous Chapters, which showed that personality traits and risk aversion explain observed labour market flows in Zimbabwean manufacturing, we provide joint estimates of the effects of personality traits, risk and time preferences on job mobility (Table E.4). Figure 6.3 depicts the probit model marginal effects on workers' probability of moving, as a function of a set of controls including personality traits, risk, and time preferences.

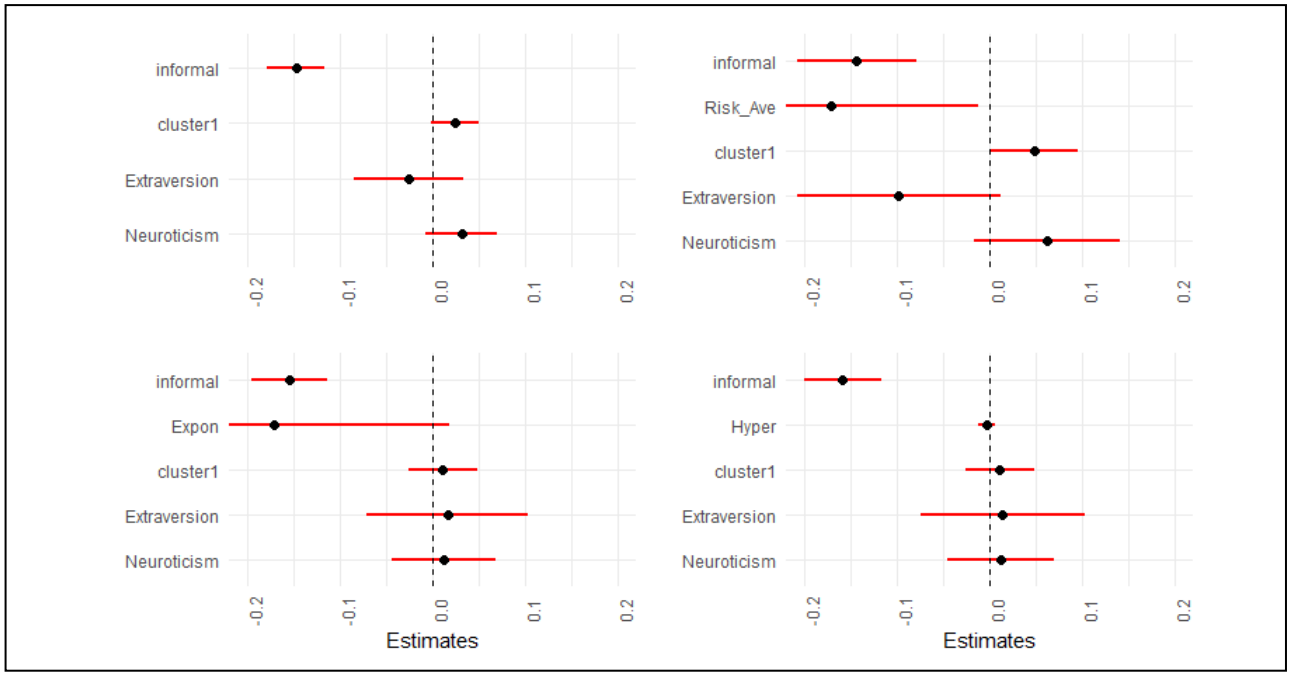


Figure 6.3: Marginal effects on Job Mobility: personality traits, risk and time preferences

Source: Author, 2019.

Our results indicate a significant negative relationship between risk aversion and job mobility. Increasing risk aversion by a unit reduces the propensity to change jobs by about 17%, holding other covariates constant. This relationship is robust to different specifications, accounting for personality traits variables (column 3 to 6). Interestingly, after controlling for risk aversion, extraversion becomes significant and negatively explains job mobility. Our results find empirical support in the literature on the effects of risk aversion on job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016).

In respect of time preferences variables, exponential discount rates have a positive significant relationship with one's probability of moving. The same direction of relationship is returned for

hyperbolic discount rates; however, it is insignificant. The results suggest that impatient individuals are less likely to move compared to the patient. Theoretically, van Huizen & Alessie (2015) argue that patience has an ambiguous relationship with job mobility; it positively relates to job arrival rates, but has a negative relationship with job acceptance. The implication is that patient workers are more likely to move, as they tend to have high on-the-job search intensity. Our results support this line of argument; impatient workers are less likely to invest in job search activities, which reduces the incidence of new job offers. To this extent, impatience may result in workers staying. This may be the case of Zimbabwean labour markets where job opportunities are scarce, and search activities may not always yield positive results.

6.4 CONCLUSION AND DISCUSSION

In this study, we follow recent evidence that confirms the significance of behavioural and psychological attributes in the analysis of labour markets. Much of this evidence, however, investigates different behavioural measures in isolation. Against this backdrop, we provide a reconciliation of the work we have done so far by providing joint estimates of personality traits, and experimentally elicited measures of risk and time preferences on three main employment outcomes: sectoral occupation, earnings, and job mobility. Our analysis shows significant joint effects of different behavioural measures in explaining Zimbabwean manufacturing employment outcomes. We find strong evidence for the simultaneous inclusion of different measures of heterogeneity in human behaviour in modelling labour market outcomes.

Our estimation results show that - across different models - personality traits variable retain the same direction of relationship even after including risk and time preferences. We however, report contrasting evidence - first in terms of the relationship between risk aversion and workers' occupational sector - and secondly between time preferences and job mobility. Risk averse individuals are more likely to select into informal sector occupations relative to the formal sector, and the relationship is significant for both forms of informal employment. These findings could reflect the different contexts within which the studies were conducted. In particular, given Zimbabwe's unique economic circumstances, the results could signify how environmental circumstances interact with individuals' behaviours to influence labour market choices and the associated outcomes. Overall, we find evidence to suggest that accounting for different behavioural measures help account for residual differences that would otherwise be unexplained, even by a rich set of control variables.

CHAPTER 7

CONCLUSIONS AND IMPLICATIONS OF THE STUDY

7.1 INTRODUCTION

This dissertation consists of five Chapters that examine the role of behavioural and psychological attributes on employment outcomes within a developing country context. Chapter 2 and Chapter 3 focused on developing measures of personality traits and empirically examined their role in explaining workers' occupational selection, earnings, and job mobility. We confirm prominent differences in the distribution of personality traits by gender and age. We show that personality traits explain employment outcomes, and their effects differ depending on sector of employment and firm-specific experiences. Chapter 4 used incentivised experiments to construct the Arrow-Pratt measure of risk aversion; we found that more risk averse workers are less likely to experience job mobility. Chapter 5 constructs measures of workers' time preferences and examined whether individuals' patience levels explain outstanding wages. Using both the exponential and hyperbolic discount rates, we found a positive association between outstanding salaries and patience, the relationship is however, statistically insignificant. In Chapter 6, we combined the behavioural and psychological measures and show that they jointly explain sectoral selection, earnings, and job mobility. Overall, the present dissertation offers support for the inclusion of behavioural and psychological attributes in models that investigate individuals' labour market outcomes.

7.2 RESEARCH CONTRIBUTION

This research adds to our current understanding of what determines success in developing countries labour markets. We address one of the challenging aspects[21] of research of this nature by introducing a novel data set: the Matched Employer-Employee Panel Data Set for Labour Market Analysis in Zimbabwe. The data captures individuals' behavioural and psychological attributes that are relevant to the analysis of labour markets. We provide evidence on the nature and distribution of behavioural and psychological attributes amongst a sample of Zimbabwean adult working population. We then address the geographical bias in the empirical literature on the role of personality traits, risk and time preferences on labour market outcomes, by providing evidence for a developing country, Zimbabwe. We provide insights on the relative importance of these attributes and shed light on the potential channels through which they influence employment outcomes in an environment characterised by economic uncertainty.

Specifically, Chapter 2 advances knowledge on the determination of personality traits using reduced item instruments within a developing country context. We show that the 15-item Big Five personality instrument can capture the core personality characteristics that can broaden our understanding of

[21] Simultaneously accounting for the role of unobservable human behavioral and psychological attributes in economic models.

sources of unobservable human heterogeneity. This provides the basis for analysing individuals' employment outcomes. Chapter 3 provides the first evidence on the role of personality traits (measured using a reduced item instrument) in explaining sectoral selection decisions, earnings and job transitions in Zimbabwe. We examine the static and dynamic aspects of Zimbabwean labour markets and show that personality traits are an important variable that explains variation in individuals' economic outcomes. By accounting for endogenous sectoral selection in the earning equation, we show that personality traits have both a direct and indirect effect on earnings. Our analysis focuses on both formal and informal labour markets, covering different industrial subsectors. The Chapter provides an integrated analysis that contributes to a deeper understanding of income distribution in developing country labour markets.

The fourth Chapter contributes to both the risk preference and job mobility literature. We show that incentivised lab-in-the-field experiments can be used to elicit for individuals' risk preferences. Most studies rely on convenience samples (usually students) but we use workers in the workplace. In addition, our experimental approach eliminates biases associated with hypothetical gambles and survey questions. We provide the first evidence on the role of risk preferences in explaining job mobility under conditions of uncertainty.

Chapter 5 contributes to the time preferences literature first by addressing the subjective nature of the survey type of time preferences measures. We use experimental data to elicit for individuals time preferences, computing both the exponential and hyperbolic discount rates to take into account present biasedness and time inconsistency. We further contribute to the role of patience in explaining outstanding salaries, and this is the first such study to do that.

Overall, by investigating both the static and dynamic aspects of labour markets, we hope to advance our understanding of the role of behavioural and psychological attributes on employment outcomes. We address the empirical gap in the context of developing countries, extending this research to Zimbabwe, a developing country going through tough economic times. We thus provide new evidence within a different context, and show that behavioural measures particularly explain observed choices and associated outcomes in labour markets.

7.3 SUMMARY OF FINDINGS

7.3.1 Personality traits in the Zimbabwean manufacturing sector

Chapter 2 sheds light on the determination of personality traits, using a reduced item instrument in a different geographical context. We used self-reported personality data, captured using a 15-item Big Five personality inventory that can be easily accommodated in a multi-module survey of labour markets. We employ CFA to extract five personality factors: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. These define the Big Five personality traits. We check for, and confirm, that our factor model passes model fit, and the factors satisfy requirements for internal reliability. We further examine how these factors are distributed by

a set of demographic factors. We found that personality traits vary by one's age, their gender, ethnicity, and geographical location. Overall, the study formed the basis of analysing the role of personality traits on employment outcomes.

7.3.2 Personality traits and labour market outcomes in Zimbabwe

Chapter 3 addressed the role of personality traits in explaining the static and dynamic aspects of Zimbabwean labour markets. In the models that we estimated, we followed a basic approach of estimating standard economic models and we control for the Big Five personality traits. The first part of this Chapter estimated workers' selection into occupational sectors, using a multinomial logit model. We found that individuals who score high in Openness, Agreeableness and Neuroticism are more likely to be in informal sector occupations (both self-employed and informal employment), relative to formal sector employment. On the contrary, those who scored high in Conscientiousness and Extraversion had a higher likelihood of formal employment relative to informal sector activities.

The second part of Chapter 3 estimated the augmented Mincer earnings equation (Mincer, 1974), with controls for personality traits. We found that more Extraverted individuals earn less in the labour markets and, surprisingly, Neuroticism positively relates to wages. Using Durbin-McFadden methodology (McFadden, 1973), we account for endogenous selection in the earnings equation, finding an indirect effect of personality traits on earnings through sectorial occupation. The third part followed literature showing that personality traits determine individuals job changing behaviour (Zimmerman, 2008); we investigated the role of personality traits in explaining job mobility in Zimbabwe. We found significant interaction effects between personality traits and employment shocks. The result suggests that - depending on firm-specific experiences - personality traits shape individuals mobility decisions. This study contributes to the literature in the context of a developing country, characterised by economic uncertainty, by integrating insights from personality psychology into mainstream economic models that investigate labour market outcomes.

7.3.3 Risk aversion and Job Mobility in Zimbabwe

Chapter 4 examined the role of risk aversion on job mobility in the Zimbabwean labour markets. The first part of the study focused on constructing the Arrow-Pratt measure of absolute risk aversion, using data elicited from a lab-in-the-field experimental task with real monetary payoffs. The second part followed van Huizen & Allise (2016) and extends a job mobility model in which risk aversion can affect job mobility through on-the-job search and job acceptance. We argued that there exists search and information frictions, which makes changing jobs inherently risky. The empirical analysis demonstrated the significance of accounting for heterogeneity in risk preferences in estimating job mobility in the Zimbabwean manufacturing sector, over and above the traditional economic variables. Risk averse individuals are less likely to experience job mobility relative to their risk tolerant peers. We account for the role of unobservables and estimated a fixed effects probit model with industrial subsector as the fixed parameter; we found that the effect of risk aversion is robust.

7.3.4 Outstanding salaries: Do time preferences matter?

Chapter 5 investigated the relationship between time preferences and individuals' labour market behaviour. Specifically, we elicited for worker's time preferences from a simple choice task with monetary rewards, and used the measures to examine outstanding wages amongst a sample of Zimbabwean manufacturing workers. We computed the patience measures, both the exponential and hyperbolic formulations, to allow for time inconsistences and present biasedness (Doyle, 2013). We estimated a probit model of outstanding wages accounting for traditional economic variables that influence individuals' labour supply decisions, and controlled for time preferences. We found that job characteristics (in particular tenure, employment shocks, industrial subsector, and earnings) explain outstanding wages. Our patience measures carry the expected signs but enter the regressions insignificantly. We argue that this could be an artefact of sample selection as impatient individuals might have left the firm already. The study sheds insights on individuals' labour supply decisions in an environment characterised by a slack labour market. In particular, we identify some of the factors that explain why individuals continue to commit their labour services even when their employers owe them unpaid wages.

7.3.5 Personality traits, Risk and Time Preferences: Labour Market Analysis in Zimbabwe.

In order to further deepen our understanding of the role of behavioural and psychological attributes, Chapter 6 provides a reconciliation of what has often been neglected in the empirical literature. We provided joint estimates on the effect of behavioural and psychological attributes on three main employment outcomes: sectoral occupation, earning, and job mobility. Essentially, we replicated the analysis in Chapter 3 but, in addition to personality traits, we account for heterogeneity in risk and time preferences. We found that in addition to personality traits, risk and time preferences explain workers occupational sector. Risk averse workers and the impatient are more likely to be involved in informal sector activities, relative to formal sector employment. In analysing earnings, we found that personality traits and hyperbolic discount rates (excepting risk aversion) explain manufacturing sector earnings. The results suggest that short run impatience explains higher earnings, and this relationship is robust to an inclusion of personality trait variables. Estimates of job mobility show that both risk and time preferences explain job turnover. Risk averse workers are less likely to move compared to their risk loving peers; the impatient - as captured by exponential discount rates - are less likely to move. Our findings underscore the need to account for both sets of behavioural measures in models that estimate individual economic outcomes.

7.4 RESEARCH IMPLICATIONS

The main aim of this research was to investigate the role of behavioural and psychological attributes on employment outcomes within an economic environment characterised by uncertainty. While traditional economic variables (including human capital, job, and firm characteristics) remain relevant and significant factors in explaining variations in economic outcomes, they do not exhaustively

account for the observed differences in labour market outcomes. The results presented in this dissertation show that that personality traits, risk and time preferences are important variables in understanding variations in individuals' labour market outcomes. Studies on individuals life outcomes - including those related to labour markets - can benefit from accounting for the role of these unobservable individual characteristics. We discuss the key implications of our findings.

Chapter 2 finds empirical support for the notion that reduced item instruments (15-item BFI) can be an efficient way of capturing the Big Five personality traits, especially in multi-module surveys (Gosling *et al*., 2003; Rammstedt & John, 2007). This has practical implications on the development and growth of this kind of research in developing countries. Despite the potential costs associated with short instruments, including failure to adequately capture all facets of the Big Five personality traits, the study shows that economically meaningful measures of individuals' personality attributes can be captured using 15 personality statements. The study shows that their distribution mirrors the global distribution of the Big Five personality traits in respect of age and gender (Schwaba & Bleidorn, 2017; Soto *et al*., 2011; Soto & Tackett, 2015).

Indeed, in Chapter 3, the study empirically confirms that the personality trait measures explain urban labour markets within a developing country context. Personality traits explain occupational sector, earnings, and job mobility. In respect of sectoral occupation, the results find support in the attraction-selection-attrition model (Schneider, 1987) and the person-environment fit theory (Caplan, 1987; Jansen & Kristof-Brown, 2006). Informal firm owners are more likely to recruit individuals with similar personality traits to them. Taken differently, there could be a selection effect of personality into occupations. The study findings are comparable to those reported for a developing country, Madagascar, where Conscientiousness and Openness are associated with formal sector employment (Villa & Sahn, 2015).

Chapter 4 showed that incentivised experiments represent an effective way of capturing heterogeneity in risk preferences; they address potential weaknesses associated with survey questions and hypothetical gambles (Holt & Laury, 2002, 2014; Lönnqvist *et al*., 2015). In addition, consistent with earlier studies on the effects of risk aversion on job mobility (Argaw *et al*., 2017; van Huizen & Alessie, 2016), Chapter 4 shows that risk tolerant individuals are more likely than their risk averse peers to experience job mobility.

At the practical level, an understanding of human behaviour can lead to better policies. Policy makers aiming to explore a more nuanced data-driven approach to policy making should consider the drivers of individual decisions and behaviours rather than making assumptions of how they should act. In the design of social protection policies (e.g. pension schemes) an understanding of individuals' risk and time preferences, for instance, may be key. Through integrating insights from this study, governments can better anticipate the behavioural consequences of a policy, and ultimately design and deliver effective policies that improve the welfare of citizens.

By combining insights from personality psychology and advanced machine learning, it is entirely possible for behavioural economists to design effective policies that can solve problems previously conceived to be intractable. While the possibilities are vast, our work speaks to how firms and government (employers in general) can use behavioural insights to match individuals to optimal jobs in the recruitment process. For example, in uncertain economic environments like Zimbabwe, growing firms or start-ups may benefit from recruiting individuals who are willing to take responsibility and are open to ideas in managerial positions. The ability to identify opportunities and develop strategies in such economic contexts may - in particular - be the difference between business failure and success. In addition, by allocating individuals to occupations and tasks that benefit most from their personality traits, firms can improve worker productivity, which has a potential of narrowing wage inequality at the national level.

Central to the success of any organisation is the ability to retain the most productive workers. Personality traits enhance workers' interaction within and outside of the workplace; how individuals develop working relations, in particular, may be of paramount importance to the performance of the firm. Chapter 3 suggests that personality traits shape individuals mobility decisions: there is ample evidence in the empirical literature showing that Neuroticism, Extraversion and Conscientiousness affect workers' job satisfaction (Judge *et al*., 2002) which informs one's intentions to quit (Eisenberger *et al*., 2001; Van Vianen *et al*., 2003; Zimmerman, 2008). Firms can effectively minimise the costs associated with job turnover by factoring personality traits during the recruitment process. Overall, the thesis supports the notion that personality traits, risk and time preferences are important constructs with both theoretical and practical implications in individuals' economic outcomes. They indeed provide a comprehensive framework of describing an individual, the similarities and differences, which are incapable of being identified using traditional economic variables.

7.5 CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The dissertation offers a novel view on the role of behavioural and psychological attributes in the context of an emerging economy's labour market, under conditions of economic uncertainty. Utilising a nationally representative matched employer-employee panel data set, we show that personality traits, risk, and time preferences are relevant to the analysis of labour markets. They explain sectoral selection, earnings, and job mobility. We show that - unlike traditional classical economic models that hinge on the assumption of rationality - allowing for heterogeneity in behavioural and psychological attributes increases our understanding of real world life situations. In particular, we can explain why individuals' economic outcomes may differ, even within a given range of human capital variables.

This dissertation focused on individuals' employment outcomes, using data captured post labour market entry, and our behavioural measures were captured in 2015. It is plausible that individuals'

choices regarding investment in human capital is partly a function of their personality traits, risk and time preferences. Longitudinal data sets that trace individuals' life paths over time - including before labour market entry - may enrich our analysis. That leads to interesting questions for future research, including stability of personality traits and if their development is affected by life events. In addition, that offers the possibility of examining how they predict human capital investments and how that may indirectly filter into individuals economic outcomes. In respect of economic preferences, studies increasingly use multi list lotteries: given resource availability, the use of such measures may further deepen our understanding of developing countries labour markets.

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APPENDICES

Appendix A.

Table A.1: The NEO- PI- R by Costa and McCrae (2008)

Big Five trait	Facets	Facet adjectives
Extraversion	Gregariousness	*sociable, open-hearted, epicurean, talkative, spontaneous*
	Assertiveness	*aggressive, dominating, confident, strong, enthusiastic*
	Activity	*energetic, hurried, fast, decided, enthusiastic, aggressive, active*
	Excitement-seeking	*bold, adventurous, charming, presentable, courageous, smart*
	Positive emotions	*enthusiastic, waggish, bragging, spontaneous, optimistic, cheerful*
	Warmth	*friendly, kind, sociable, glad, affectionate, open-hearted*
Agreeableness	Trust	*suspicious, cautious, pessimistic, insensitive forgiving, credulous, peaceful*
	Straight forwardness	*complicated, pretentious, manipulative, unsettling, misleading, artful, despotic, constant, sincere*
	Altruism	*egocentric cordial, pitiful, gentile, generous, gentle, tolerant*
	Compliance	*obstinate, demanding, stubborn, anxious, impatient, intolerant, brutal, insensitive, sensible, tolerant*
	Modesty	*affected, manipulative, assertive, quarrelsome, confident, aggressive, idealistic , modest*
	Tender-mindedness	*inconstant friendly, cordial, empathic, pitiful, gentile*
Conscientiousness	Competence	*confused effective, confident, perfectionist, versatile, smart*
	Order	*inattentive, negligent organized, meticulous, effective, accurate, methodic*
	Dutifulness	*defensive, bewildered, careless, easy-going, absent, quarrelsome, meticulous, scrupulous*
	Achievement-striving	*disinterested, unmotivated, conscientious, ambitious, diligent, enterprising, decided, tenacious*
	Self-discipline	*indolent, absent, organized, effective, energetic, serious, hardworking*
	Deliberation	*hasty, impulsive, careless, impatient, immature, capricious elaborated, thoughtful*
Neuroticism	Anxiety	*anxious, worried, concerned, tensed, nervous*
	Angry hostility	*restless, irritable, anxious, excitable, moody, tensed*
	Depression	*worried, pessimistic, indisposed, anxious*
	Self-consciousness	*self-conscious, shy, distrustful, defensive, inhibited*
	Impulsiveness	*moody, irritable, sarcastic, self-centred, noisy, hasty, excitable*
	Vulnerability	*lucid, confident, trustful, operative, vigilant negligent*
Openness	Ideas	*disinterested, conservative, idealistic, interested, curious, original, imaginative, introspective*
	Fantasy	*dreamy, imaginative, waggish, roguishly, idealistic, artistic*
	Aesthetics	*imaginative, artistic, original, enthusiastic, inventive, idealistic, versatile*
	Actions	*moderate, curious, imaginative, adventurous, optimistic, talkative, open-hearted*
	Feelings	*excitable, spontaneous, introspective, imaginative, affectionate, talkative, open-hearted,*
	Values	*conservative, cautious unconventional, rakish*

Table A.2: Sample descriptive statistics

	Total		**Formal**		**Informal**		
	mean	s.d.	mean	s.d.	Mean	s.d.	*p*-values
Age	40.12	11.67	41.62	11.57	33.36	9.55	0.000
Married	0.80	0.39	0.83	0.38	0.59	0.49	0.000
Male	0.81	0.39	0.80	0.40	0.84	0.36	0.115
Tenure	11.48	10.58	12.72	10.93	5.79	5.94	0.000
Experience	5.34	6.86	5.55	7.18	4.35	4.95	0.001
Years education	11.23	2.29	11.26	2.40	11.08	1.74	0.003
Household size	4.45	1.78	4.54	1.98	4.06	1.63	0.000
M/Earnings	363.06	404.62	379.24	378.47	287.70	503.90	0.268

Table A.3: The BFI-15 and item descriptive statistics

Big Five Trait	Item	Statement	KMO	Mean	SD	skew	kurtosis
Extraversion	Extr1	Do you talk a lot?	0.67	2.9244	1.6712	0.071	-1.5653
	Extr2	Do you start conversations?	0.73	4.1585	1.3005	-1.2709	0.3807
	Extr3	Do you like being the center of attention?	0.72	2.4334	1.6332	0.5617	-1.2776
Conscientiousness	Consc1	Do you leave your belongings around?	0.60	3.8091	1.6501	-0.8677	-0.9762
	Consc2	Do you pay attention to details?	0.69	4.7335	0.791	-3.0853	9.2745
	Consc3	Do you get chores done right away?	0.72	4.593	0.9326	-2.2496	4.376
Openness	Open1	Are you imaginative/creative?	0.67	4.4262	1.1314	-1.8433	2.3297
	Open2	Do you think about things a lot?	0.61	3.9652	1.4357	-1.0149	-0.3689
	Open3	Are you full of ideas?	0.73	4.2281	1.2808	-1.4183	0.7603
Agreeableness	Agre1	Are you interested in people?	0.71	4.5114	1.0439	-2.0614	3.3372
	Agre2	Do you care a lot about other people's problems?	0.76	4.7323	0.7768	-2.9933	8.7405
	Agre3	Do you have a soft heart?	0.74	4.7647	0.764	-3.4198	11.55
Neuroticism	Neur1	Do you worry about things?	0.61	1.3532	1.2028	0.1334	0.0332
	Neur2	Do you get upset easily?	0.58	1.6217	0.7591	-1.0629	0.0397
	Neur3	Do you change your mood a lot?	0.59	1.3302	1.3893	0.5831	0.0326

Table A.4: Confirmatory Factor Analysis results (CFA Model 1)

P-value (Chi-square)		0.000		
Comparative Fit Index (CFI)		0.673		
Tucker-Lewis Index (TLI)		0.570		
RMSEA		0.070		
SRMR		0.064		
latent variables				
Agreeableness =~	Estimate	Std.Err	z-value	p-value
agre1	0.461	0.036	12.729	0.000
agre2	0.302	0.026	11.758	0.000
agre3	**0.175**	0.024	7.374	0.000
Conscientiousness =~				
consc2	0.361	0.031	11.665	0.000
consc3	0.386	0.035	11.139	0.000
consc1	**-0.211**	0.057	-3.724	0.000
Extraversion =~				
extr2	0.673	0.052	12.946	0.000
extr1	0.557	0.057	9.781	0.000
extr3	0.431	0.055	7.827	0.000
Neuroticism =~				
neur2	1.075	0.089	12.066	0.000
neur3	0.890	0.074	12.089	0.000
neur1	**0.241**	0.042	5.761	0.000
Openness =~				
open1	0.598	0.040	14.931	0.000
open3	0.671	0.045	14.863	0.000
open2	0.362	0.047	7.646	0.000

NB: The latent variable estimates in bold are dropped

Table A.5: Modification indices

lhs	rhs	M.I.
consc2 ~~	open1	43.622
Neuroticism =~	extr2	40.262
agre2	consc2	31.698
Neuroticism =~	open1	28.917
Conscientiousness =~	agre1	26.918
Conscientiousness =~	agre2	26.917
open1	Open2	23.197
Neuroticism =~	extr1	19.396
Agreeableness =~	extr1	16.831
Extraversion =~	open1	16.717

Table A.6: CFA Model 2 Results

Chi-square		0.000		
Comparative Fit Index (CFI)		0.963		
Tucker-Lewis Index (TLI)		0.963		
RMSEA		0.031		
SRMR		0.027		
latent variables				
Agreeableness =~	Estimate	Std.Err	z-value	p-value
agre1	0.541	0.046	11.879	0.000
agre2	0.261	0.026	9.939	0.000
Conscientiousness =~				
consc2	0.364	0.040	9.136	0.000
consc3	0.362	0.042	8.679	0.000
Extraversion =~				
extr2	0.670	0.051	13.258	0.000
extr1	0.579	0.056	10.396	0.000
extr3	0.415	0.054	7.755	0.000
Neuroticism =~				
neur2	1.202	0.163	7.375	0.000
neur3	0.781	0.107	7.324	0.000
Openness =~				
open1	0.600	0.047	12.884	0.000
open3	0.721	0.055	13.058	0.000

Figure A.1: Confirmatory factor structure

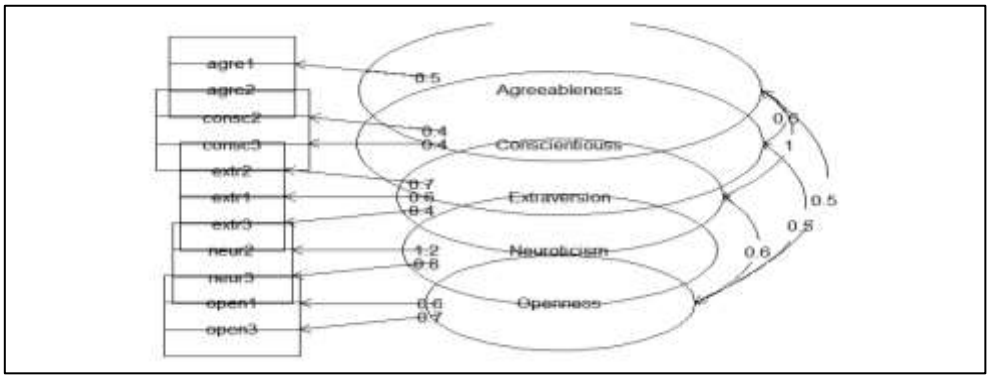

Table A.7: Reliability analysis

	Raw alpha	Std.alpha
Agreeableness	0.69	0.70
Conscientiousness	0.72	0.73
Extraversion	0.61	0.65
Neuroticism	0.89	0.90
Openness	0.69	0.70

Figure A.2: Distribution of personality traits by gender, age, ethnicity and location

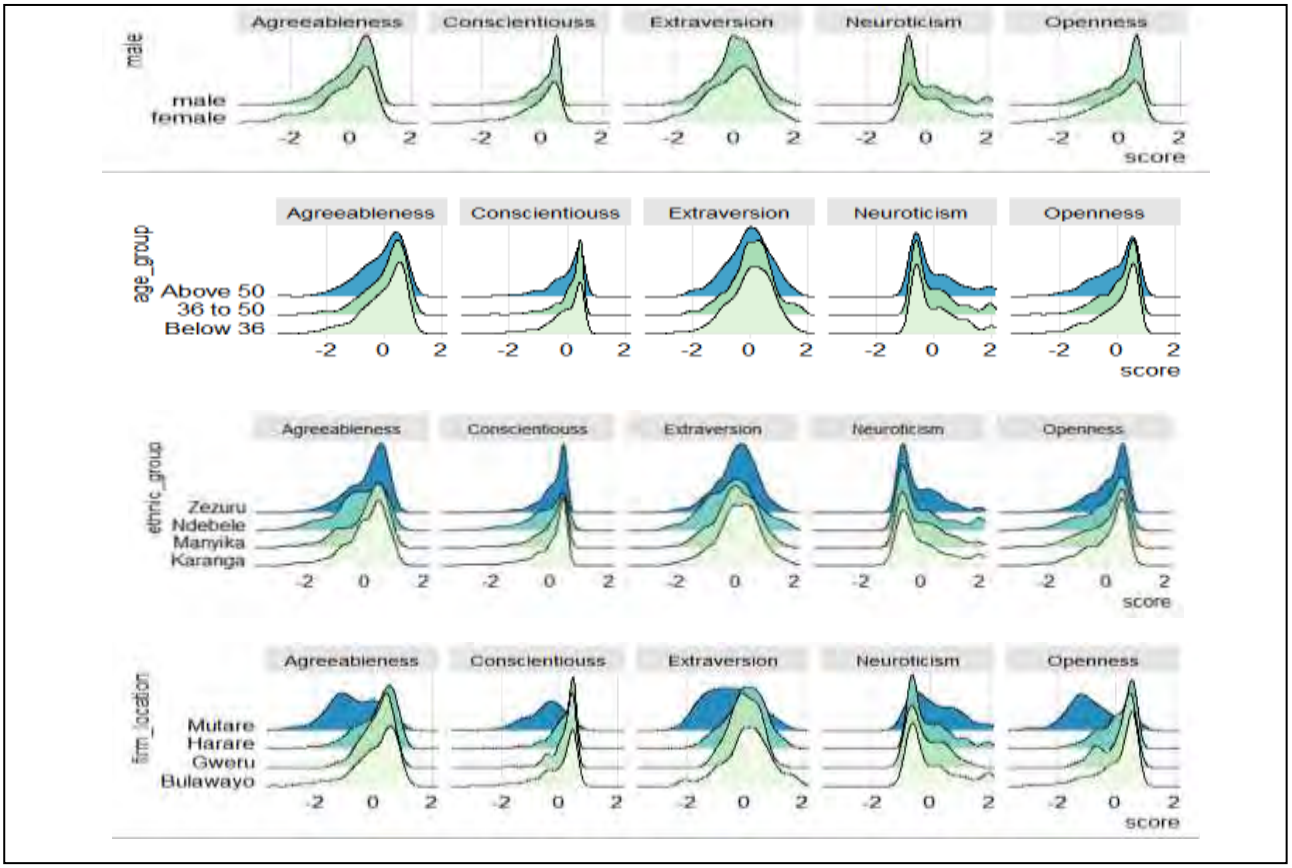

Table A.8: Personality traits and demographic characteristics

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
age	0.020**	0.014*	0.025**	0.009	0.036***
	(0.010)	(0.008)	(0.010)	(0.011)	(0.009)
agesqr	-0.247**	-0.150	-0.316***	-0.097	-0.432***
	(0.114)	(0.096)	(0.115)	(0.123)	(0.107)
male	0.182***	0.099**	0.048	-0.220***	0.190***
	(0.046)	(0.039)	(0.047)	(0.050)	(0.043)
Ndebele	-0.328***	-0.253***	-0.230***	0.045	-0.144***
	(0.055)	(0.046)	(0.055)	(0.059)	(0.051)
Manyika	0.053	0.065	0.068	0.046	0.047
	(0.053)	(0.045)	(0.054)	(0.057)	(0.050)
Karanga	-0.050	-0.027	0.035	0.130**	-0.017
	(0.053)	(0.044)	(0.053)	(0.057)	(0.049)
Foreigner	-0.437	-0.329	-0.186	0.382	-0.506
	(0.329)	(0.276)	(0.332)	(0.356)	(0.308)
Bulawayo	0.145***	0.069*	0.172***	0.059	0.103**
	(0.045)	(0.038)	(0.045)	(0.049)	(0.042)
Gweru	0.109	0.140	-0.026	-0.203*	0.149
	(0.104)	(0.087)	(0.104)	(0.112)	(0.097)
Mutare	-0.773***	-0.619***	-0.583***	0.187*	-0.846***
	(0.093)	(0.078)	(0.094)	(0.100)	(0.087)
informal	-0.044	-0.013	0.018	0.084	0.174***
	(0.050)	(0.042)	(0.050)	(0.054)	(0.047)
Num.obs.	1655	1655	1655	1655	1655

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Appendix B.

Table B.1: Descriptive statistics of key variables

	Total		Formal		Informal		
	mean	s.d.	mean	s.d.	mean	s.d.	*p*-values
Age	40.12	11.67	41.62	11.57	33.36	9.55	0.000
Married	0.80	0.39	0.83	0.38	0.59	0.49	0.000
Male	0.81	0.39	0.80	0.40	0.84	0.36	0.115
Tenure	11.48	10.58	12.72	10.93	5.79	5.94	0.000
Experience	5.34	6.86	5.55	7.18	4.35	4.95	0.001
Years education	11.23	2.29	11.26	2.40	11.08	1.74	0.003
Household size	4.45	1.78	4.54	1.98	4.06	1.63	0.000
M/Earnings	363.06	404.62	379.24	378.47	287.70	503.90	0.268

Table B.2: Estimated Multinomial Logit Coefficients on Selection into Employment

Dependent variable: Occupational sector

	Column 1		Column 2		Column 3	
	IE	**SE**	**IE**	**SE**	**IE**	**SE**
(Intercept)	2.099	-8.681***	2.404	-8.880***	2.398	-8.366***
	(2.044)	(2.255)	(2.116)	(2.310)	(2.030)	(2.261)
age	-0.211***	0.271***	-0.222***	0.288***	-0.212***	0.266***
	(0.062)	(0.089)	(0.066)	(0.093)	(0.063)	(0.089)
agesqr/1000	1.236	-3.893***	1.394	-4.096***	1.230	-3.839***
	(0.806)	(1.102)	(0.857)	(1.146)	(0.809)	(1.102)
male	0.184	0.332	0.148	0.272	0.237	0.345
	(0.251)	(0.270)	(0.266)	(0.279)	(0.256)	(0.274)
married	-0.299	0.008	-0.286	-0.010	-0.358	-0.020
	(0.248)	(0.320)	(0.261)	(0.327)	(0.251)	(0.321)
hhsize	-0.162***	0.013	-0.165***	-0.001	-0.166***	0.013
	(0.056)	(0.057)	(0.058)	(0.058)	(0.056)	(0.057)
yrs_educ	0.406	-0.135	0.386	-0.131	0.364	-0.157
	(0.306)	(0.229)	(0.316)	(0.237)	(0.302)	(0.228)
educsqr	-0.036***	0.000	-0.036**	-0.001	-0.035**	0.001
	(0.014)	(0.010)	(0.014)	(0.010)	(0.014)	(0.010)
Ndebele	0.370	-0.711*	0.239	-0.827**	0.347	-0.702*
	(0.376)	(0.369)	(0.390)	(0.380)	(0.378)	(0.369)
Manyika	0.427*	0.308	0.477*	0.357	0.401	0.284
	(0.254)	(0.253)	(0.262)	(0.261)	(0.255)	(0.253)
Karanga	0.034	-0.351	0.003	-0.361	-0.012	-0.385
	(0.293)	(0.290)	(0.303)	(0.296)	(0.296)	(0.291)
Foreigner	0.598	-10.952***	0.724	-11.343***	0.706	-10.858***
	(1.292)	(0.000)	(1.329)	(0.000)	(1.274)	(0.000)
Harare	2.748***	3.519***	2.815***	3.519***	2.812***	3.457***
	(0.541)	(1.013)	(0.564)	(1.017)	(0.554)	(1.014)
Bulawayo	1.832***	3.678***	1.776***	3.545***	1.903***	3.625***
	(0.584)	(1.033)	(0.608)	(1.038)	(0.593)	(1.034)
Openness			2.832***	2.980***		
			(0.438)	(0.454)		
Conscientious			-3.774***	-4.947***		
			(0.902)	(0.926)		
Extraversion			-9.261***	-11.780***	-0.831***	-0.407
			(2.207)	(2.250)	(0.295)	(0.311)
Agreeableness			8.467***	11.473***		
			(2.250)	(2.302)		
Neuroticism			5.395***	6.912***	0.601***	0.361*
			(1.297)	(1.321)	(0.202)	(0.205)
cluster1					0.367***	0.240*
					(0.135)	(0.143)
AIC	1628.191	1628.191	1554.042	1554.042	1627.180	1627.180
BIC	1779.715	1779.715	1759.681	1759.681	1811.173	1811.173
Log Likelihood	-786.096	-786.096	-739.021	-739.021	-779.590	-779.590
Deviance	1572.191	1572.191	1478.042	1478.042	1559.180	1559.180
Num. obs.	1655	1655	1655	1655	1655	1655

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.3: Personality Traits and Earnings: 50th Quantile

	1	2	3	4	5	6	7
(Intercept)	4.889***	4.879***	4.914***	4.879***	4.901***	4.900***	4.923***
	(0.215)	(0.259)	(0.230)	(0.212)	(0.242)	(0.263)	(0.264)
male	0.269***	0.264***	0.254***	0.266***	0.256***	0.249***	0.245***
	(0.041)	(0.038)	(0.040)	(0.041)	(0.040)	(0.042)	(0.041)
married	0.075*	0.088**	0.083*	0.078*	0.077*	0.070*	0.073*
	(0.042)	(0.040)	(0.043)	(0.042)	(0.041)	(0.037)	(0.040)
age	0.021**	0.019**	0.017*	0.019**	0.018**	0.020**	0.020**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
agesqr	-0.194*	-0.160	-0.148	-0.164*	-0.151	-0.179*	-0.188*
	(0.101)	(0.106)	(0.103)	(0.099)	(0.100)	(0.098)	(0.101)
experience	0.005	0.004	0.005	0.005	0.006	0.006	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
expersq	0.008	0.003	0.007	0.004	-0.002	-0.001	0.005
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
tenure	0.005*	0.004	0.004*	0.004*	0.004*	0.004	0.004*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
yrs_educ	-0.096***	-0.093***	-0.089***	-0.090***	-0.089***	-0.091**	-0.096***
	(0.024)	(0.035)	(0.029)	(0.024)	(0.032)	(0.037)	(0.037)
educsqr	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
training	0.175***	0.163***	0.180***	0.176***	0.168***	0.184***	0.188***
	(0.043)	(0.043)	(0.042)	(0.045)	(0.043)	(0.046)	(0.045)
informal	-0.389***	-0.380***	-0.395***	-0.391***	-0.393***	-0.390***	-0.391***
	(0.056)	(0.053)	(0.058)	(0.056)	(0.054)	(0.057)	(0.052)
Openness	0.013					0.061	
	(0.017)					(0.050)	
Conscientious		0.041*				-0.045	
		(0.021)				(0.117)	
Extraversion			-0.004			-0.310	-0.082**
			(0.017)			(0.287)	(0.036)
Agreeableness				0.013		0.265	
				(0.016)		(0.289)	
Neuroticism					-0.006	0.180	0.043*
					(0.015)	(0.171)	(0.023)
cluster1							0.044***
							(0.015)
Num. obs.	1453	1453	1453	1453	1453	1453	1453
Percentile	0.500	0.500	0.500	0.500	0.500	0.500	0.500

***p < 0.01, **p < 0.05, *p < 0.1

Table B.4: Personality Traits and Earnings: 75th Quantile

	1	2	3	4	5	6	7
(Intercept)	5.299***	5.336***	5.379***	5.362***	5.356***	5.325***	5.219***
	(0.286)	(0.263)	(0.184)	(0.233)	(0.218)	(0.162)	(0.249)
male	0.141***	0.136***	0.147***	0.148***	0.150***	0.136***	0.155***
	(0.041)	(0.045)	(0.045)	(0.041)	(0.045)	(0.042)	(0.045)
married	0.072	0.072*	0.076*	0.075*	0.073	0.095**	0.071
	(0.044)	(0.043)	(0.045)	(0.045)	(0.046)	(0.043)	(0.044)
age	0.011	0.011	0.013**	0.013*	0.014*	0.009	0.012
	(0.008)	(0.009)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
agesqr	-0.066	-0.063	-0.108	-0.100	-0.122	-0.048	-0.072
	(0.096)	(0.101)	(0.076)	(0.095)	(0.089)	(0.083)	(0.093)
experience	0.016**	0.017**	0.018***	0.018***	0.018**	0.017**	0.017**
	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)
expersq	-0.031	-0.034	-0.034	-0.035	-0.033	-0.035	-0.035
	(0.031)	(0.036)	(0.030)	(0.030)	(0.032)	(0.030)	(0.035)
tenure	0.007**	0.007***	0.009***	0.009***	0.009***	0.008***	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
yrs_educ	-0.108**	-0.117***	-0.133***	-0.131***	-0.132***	-0.106***	-0.104***
	(0.043)	(0.039)	(0.027)	(0.034)	(0.029)	(0.012)	(0.035)
educsqr	0.009***	0.010***	0.011***	0.011***	0.010***	0.009***	0.009***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
training	0.164***	0.176***	0.184***	0.177***	0.186***	0.180***	0.174***
	(0.062)	(0.053)	(0.051)	(0.050)	(0.047)	(0.049)	(0.062)
informal	-0.304***	-0.298***	-0.269***	-0.267***	-0.254***	-0.264***	-0.291***
	(0.059)	(0.072)	(0.062)	(0.065)	(0.063)	(0.068)	(0.065)
Openness	0.043**					0.057	
	(0.018)					(0.063)	
Conscientious		0.058**				0.086	
		(0.024)				(0.136)	
Extraversion			0.011			0.081	-0.082*
			(0.015)			(0.340)	(0.042)
Agreeableness				0.016		-0.149	
				(0.018)		(0.334)	
Neuroticism					-0.005	-0.067	0.035
					(0.020)	(0.200)	(0.028)
cluster1							0.054***
							(0.019)
Num. obs.	1453	1453	1453	1453	1453	1453	1453
Percentile	0.750	0.750	0.750	0.750	0.750	0.750	0.750

***p < 0.01, **p < 0.05, *p < 0.1

Table B.5: Mincer Equation with controls for interactions with informal employment

Log wage	1	2	3	4	5	6	7	8
age	0.031***	0.030***	0.031***	0.031***	0.032***	0.031***	0.029***	0.030***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Agesqr/1000	-0.393***	-0.379***	-0.383***	-0.391***	-0.398***	-0.387***	-0.369***	-0.382***
	(0.117)	(0.117)	(0.116)	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)
male	0.227***	0.220***	0.214***	0.228***	0.224***	0.232***	0.216***	0.224***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
married	0.148***	0.150***	0.153***	0.148***	0.152***	0.146***	0.153***	0.148***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
experience	0.016**	0.016**	0.016**	0.016**	0.016**	0.016**	0.016**	0.015**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
expersq	0.003	0.002	0.003	0.004	0.003	0.003	0.003	0.004
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
tenure	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
yrs_educ	-0.074*	-0.075*	-0.077*	-0.073*	-0.075*	-0.072*	-0.079*	-0.078*
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
educsqr	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
training	0.178***	0.178***	0.179***	0.178***	0.181***	0.179***	0.182***	0.182***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.051)	(0.051)
informal	-0.334***	-0.413***	-0.403***	-0.343***	-0.360***	-0.322***	-0.452***	-0.447***
	(0.062)	(0.072)	(0.065)	(0.062)	(0.063)	(0.063)	(0.086)	(0.073)
Openness		0.018					0.111	
		(0.024)					(0.071)	
informal:Openness		0.260*					0.198	
		(0.135)					(0.371)	
Conscientious			0.009				-0.062	
			(0.028)				(0.151)	
informal:Conscientious			0.439***				-0.003	
			(0.131)				(0.753)	
Extraversion				-0.020			-0.284	-0.112**
				(0.023)			(0.373)	(0.050)
informal:Extraversion				0.208***			-1.846	-0.325
				(0.079)			(1.885)	(0.246)
Agreeableness					-0.024		0.184	
					(0.024)		(0.374)	
informal:Agreeableness					0.211***		1.799	
					(0.082)		(1.908)	
Neuroticism						0.005	0.156	0.062*
						(0.022)	(0.219)	(0.034)
informal:Neuroticism						0.102	1.219	0.304*
						(0.082)	(1.116)	(0.163)
cluster1								0.042*
								(0.022)
informal:cluster1								0.321**
								(0.132)
R^2	0.199	0.202	0.206	0.203	0.203	0.200	0.213	0.210
Adj. R^2	0.193	0.195	0.199	0.196	0.196	0.193	0.201	0.201
Num. obs.	1453	1453	1453	1453	1453	1453	1453	1453
RMSE	0.620	0.619	0.618	0.619	0.619	0.620	0.617	0.617

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.6: Mincer Earnings Equation: Sectoral Selection

Dependent variable: Log Monthly earnings

	1	2	3	4	5	6	7	8
(Intercept)	4.621***	4.639***	4.631***	4.619***	4.613***	4.614***	4.720***	4.681***
	(0.352)	(0.357)	(0.353)	(0.352)	(0.352)	(0.352)	(0.361)	(0.356)
age	0.026**	0.026**	0.026**	0.026**	0.026**	0.026**	0.025*	0.026**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
agesqr/1000	-0.342**	-0.339**	-0.342**	-0.343**	-0.343**	-0.344**	-0.332**	-0.340**
	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
male	0.222***	0.221***	0.221***	0.222***	0.225***	0.226***	0.228***	0.229***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
married	0.152***	0.152***	0.152***	0.152***	0.151***	0.152***	0.150***	0.150***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
experience	0.016**	0.016**	0.015**	0.015**	0.016**	0.016**	0.016**	0.015**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
expersq	0.006	0.006	0.006	0.007	0.007	0.006	0.006	0.007
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
tenure	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
yrs_educ	-0.074*	-0.074*	-0.075*	-0.074*	-0.073*	-0.073*	-0.077*	-0.077*
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
educsqr	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
training	0.190***	0.190***	0.190***	0.190***	0.192***	0.194***	0.195***	0.195***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
DMF self emp	0.312	0.287	0.304	0.330	0.337	0.292	0.230	0.275
	(0.283)	(0.293)	(0.284)	(0.287)	(0.285)	(0.284)	(0.322)	(0.288)
DMF infor emp	-0.375**	-0.386**	-0.378**	-0.376**	-0.378**	-0.375**	-0.449**	-0.420**
	(0.164)	(0.167)	(0.164)	(0.164)	(0.164)	(0.164)	(0.176)	(0.166)
Openness		0.008					0.050	
		(0.025)					(0.085)	
Conscientious			0.011				0.023	
			(0.028)				(0.169)	
Extraversion				-0.010			-0.082	-0.093*
				(0.022)			(0.414)	(0.050)
Agreeableness					-0.020		0.006	
					(0.023)		(0.413)	
Neuroticism						0.017	0.057	0.066*
						(0.021)	(0.243)	(0.034)
cluster1								0.035
								(0.022)
R^2	0.192	0.192	0.192	0.192	0.192	0.192	0.194	0.194
Adj. R^2	0.185	0.184	0.184	0.184	0.185	0.185	0.185	0.186
Num. obs.	1446	1446	1446	1446	1446	1446	1446	1446
RMSE	0.624	0.624	0.624	0.624	0.624	0.624	0.624	0.623

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.7: Linear Probability Model on Personality and Employee Mobility.

Dependent variable : Left firm

	1	2	3	4	5	6	7	8
(Intercept)	1.106***	1.162***	1.167***	1.103***	1.131***	1.082***	1.146***	1.162***
	(0.293)	(0.295)	(0.294)	(0.292)	(0.293)	(0.294)	(0.299)	(0.297)
age	-0.020*	-0.022*	-0.021*	-0.021*	-0.021*	-0.020*	-0.021*	-0.021*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
agesqr/100	0.261**	0.281**	0.272**	0.269**	0.272**	0.256**	0.267**	0.273**
	(0.124)	(0.125)	(0.124)	(0.124)	(0.124)	(0.124)	(0.125)	(0.125)
male	-0.026	-0.037	-0.035	-0.028	-0.032	-0.023	-0.033	-0.035
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)	(0.047)
married	-0.078	-0.077	-0.083	-0.078	-0.078	-0.080	-0.084	-0.083
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
yrs_educ	-0.051	-0.050	-0.053	-0.048	-0.050	-0.049	-0.051	-0.051
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
educsqr	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
hhsize	0.009	0.009	0.008	0.009	0.009	0.009	0.009	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
log_tenure	-0.068***	-0.070***	-0.072***	-0.069***	-0.070***	-0.067***	-0.072***	-0.070***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
micro	0.199	0.186	0.190	0.204	0.197	0.206	0.198	0.189
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.134)	(0.133)
small	0.110**	0.105**	0.107**	0.110**	0.108**	0.112**	0.107**	0.107**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
medium	-0.024	-0.024	-0.024	-0.022	-0.023	-0.022	-0.022	-0.024
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.039)	(0.038)
Openness		0.034					-0.056	
		(0.025)					(0.076)	
Conscientious			0.054*				0.213	
			(0.028)				(0.158)	
Extraversion				0.030			0.395	-0.044
				(0.024)			(0.396)	(0.053)
Agreeableness					0.028		-0.407	
					(0.025)		(0.394)	
Neuroticism						0.017	-0.216	0.040
						(0.022)	(0.233)	(0.034)
cluster1								0.036
								(0.022)
R^2	0.061	0.064	0.066	0.063	0.063	0.062	0.069	0.067
Adj. R^2	0.045	0.046	0.049	0.046	0.045	0.044	0.046	0.047
Num. obs.	659	659	659	659	659	659	659	659
RMSE	0.446	0.446	0.446	0.446	0.446	0.447	0.446	0.446

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.8: Probit model marginal effects of personality, shocks on mobility

Dependent variable is Employee Mobility

	1	2	3	4	5	6	7	8
age	-0.025**	-0.029**	-0.027**	-0.026**	-0.026**	-0.025**	-0.028**	-0.028**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
agesqr/1000	0.309**	0.351**	0.329**	0.324**	0.326**	0.308**	0.344**	0.343**
	(0.134)	(0.137)	(0.135)	(0.135)	(0.135)	(0.135)	(0.137)	(0.136)
male	-0.055	-0.067	-0.063	-0.054	-0.059	-0.053	-0.066	-0.065
	(0.054)	(0.055)	(0.055)	(0.054)	(0.054)	(0.054)	(0.055)	(0.055)
married	-0.134*	-0.135*	-0.147**	-0.137**	-0.138**	-0.135*	-0.144**	-0.146**
	(0.069)	(0.069)	(0.070)	(0.069)	(0.069)	(0.069)	(0.070)	(0.070)
yrs_educ	-0.049	-0.047	-0.051	-0.045	-0.049	-0.047	-0.049	-0.049
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
educsqr	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
hhsize	0.015	0.015	0.015	0.016	0.015	0.015	0.015	0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
tenure	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Small	0.151**	0.143**	0.145**	0.149**	0.146**	0.152**	0.142**	0.145**
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.063)
Medium	-0.034	-0.035	-0.035	-0.033	-0.035	-0.033	-0.034	-0.034
	(0.043)	(0.043)	(0.043)	(0.044)	(0.043)	(0.044)	(0.044)	(0.043)
shock	0.088**	0.100**	0.094**	0.097**	0.093**	0.090**	0.099**	0.099**
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Openness		0.054*					-0.013	
		(0.028)					(0.089)	
Conscientious			0.065**				0.166	
			(0.033)				(0.186)	
Extraversion				0.035			0.288	-0.043
				(0.027)			(0.462)	(0.059)
Agreeableness					0.039		-0.302	
					(0.028)		(0.459)	
Neuroticism						0.009	-0.161	0.034
						(0.024)	(0.271)	(0.038)
cluster1								0.043*
								(0.025)
Num. obs.	536	536	536	536	536	536	536	536
Log Likelihood	-299.01	-297.21	-297.09	-298.15	-298.02	-298.94	-296.37	-296.67
Deviance	598.012	594.423	594.189	596.301	596.037	597.881	592.759	593.351
AIC	622.012	620.423	620.189	622.301	622.037	623.881	626.759	623.351
BIC	673.421	676.117	675.883	677.995	677.731	679.574	699.589	687.613

****p < 0.01, **p < 0.05, *p < 0.1*

Table B.9: Fixed effects probit model on job mobility

Left job	Estimate	Std.Err	t-value	p-value
age	-0.105	0.040	-2.626	0.008**
agesqr	1.353	0.451	2.998	0.003**
male	-0.311	0.182	-1.706	0.088*
Married	-0.265	0.198	-1.337	0.181
Yrs_educ_	-0.161	0.131	-1.230	0.219
educsqr	0.007	0.005	1.206	0.228
hhsize	0.037	0.033	1.139	0.255
tenure	-0.030	0.010	-3.079	0.002**
Extraversion	-0.005	0.199	-0.028	0.978
Neuroticism	0.100	0.128	0.784	0.433
Cluster1	0.039	0.087	0.450	0.653

Table B.10: Fixed effects probit model with analytical bias-correction: Mobility

Left job	Estimate	Std.Err	t-value	p-value
age	-0.106	0.040	-2.626	0.009**
agesqr	1.362	0.451	2.998	0.003**
male	-0.311	0.182	-1.706	0.088*
Married	-0.265	0.198	-1.337	0.181
Yrs_educ_	-0.161	0.131	-1.230	0.219
educsqr	0.007	0.005	1.206	0.228
hhsize	0.037	0.033	1.139	0.255
tenure	-0.030	0.010	-3.079	0.002**
Openness	-0.095	0.284	-0.335	0.738
Conscientious	0.367	0.588	0.625	0.532
Extraversion	0.854	1.470	0.581	0.561
Agreeableness	-0.835	1.455	-0.574	0.565
Neuroticism	-0.407	0.864	-0.471	0.637

Table B.11: Personality and employee mobility: Interacted Shocks

Dependent variable: Mobility

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
age	-0.022*	-0.027**	-0.026**	-0.023*	-0.024**	-0.021*	-0.025**	-0.025**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
agesqr/100	0.277**	0.326**	0.314**	0.293**	0.296**	0.268**	0.314**	0.310**
	(0.134)	(0.137)	(0.134)	(0.135)	(0.135)	(0.135)	(0.137)	(0.136)
male	-0.041	-0.049	-0.045	-0.040	-0.048	-0.039	-0.053	-0.049
	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)	(0.053)	(0.055)	(0.055)
married	-0.129*	-0.133*	-0.147**	-0.133*	-0.129*	-0.130*	-0.151**	-0.143**
	(0.069)	(0.069)	(0.070)	(0.069)	(0.069)	(0.069)	(0.071)	(0.070)
yrs_educ	-0.059	-0.058	-0.060	-0.055	-0.059	-0.061	-0.060	-0.063
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
educsqr	0.003	0.003	0.003	0.003	0.003	0.003*	0.003	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
hhsize	0.014	0.013	0.013	0.015	0.013	0.014	0.015	0.013
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
tenure	-0.005*	-0.005**	-0.005**	-0.005*	-0.005**	-0.005*	-0.005**	-0.005**

	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
shock	0.086**	0.100**	0.090**	0.095**	0.093**	0.090**	0.087**	0.100**
	(0.040)	(0.041)	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)	(0.041)
Openness		0.030					0.070	
		(0.040)					(0.117)	
Openness:shock		0.055					-0.224	
		(0.056)					(0.180)	
Conscientious			0.011				-0.040	
			(0.046)				(0.246)	
Conscientious:shock			0.122*				0.545	
			(0.068)				(0.374)	
Extraversion				0.036			-0.174	-0.058
				(0.039)			(0.622)	(0.081)
Extraversion:shock				0.003			1.216	0.014
				(0.054)			(0.932)	(0.118)
Agreeableness					-0.014		0.128	
					(0.040)		(0.623)	
Agreeableness:shock					0.109**		-1.145	
					(0.056)		(0.925)	
Neuroticism						0.055*	0.148	0.084
						(0.031)	(0.368)	(0.052)
Neuroticism:shock						-0.117**	-0.809	-0.117
						(0.049)	(0.546)	(0.077)
cluster1								0.028
								(0.035)
cluster1:shock								0.038
								(0.051)
Num. obs.	536	536	536	536	536	536	536	536
Log Likelihood	-303.75	-301.13	-300.01	-302.76	-300.65	-300.81	-295.55	-297.01
Deviance	607.49	602.25	600.01	605.52	601.29	601.61	591.09	594.02
AIC	627.49	626.25	624.01	629.52	625.29	625.61	631.09	626.02

***p < 0.01, **p < 0.05, *p < 0.1*

Table B.11: Linear Probability Model on Personality and Voluntary Mobility.

Linear Probability Model on Personality and employee mobility

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
(Intercept)	1.959***	1.958***	1.922***	1.993***	1.995***	1.931***	2.120***	2.127***
	(0.497)	(0.502)	(0.502)	(0.500)	(0.496)	(0.498)	(0.510)	(0.511)
age	-0.042**	-0.042**	-0.041**	-0.041**	-0.040**	-0.042**	-0.040**	-0.042**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
agesqr/100	0.434*	0.434*	0.422*	0.424*	0.405*	0.431*	0.401*	0.420*
	(0.222)	(0.223)	(0.223)	(0.222)	(0.221)	(0.222)	(0.221)	(0.222)
male	0.140*	0.140*	0.146*	0.141*	0.147*	0.142*	0.149*	0.135
	(0.084)	(0.084)	(0.085)	(0.084)	(0.083)	(0.084)	(0.084)	(0.084)
married	-0.023	-0.023	-0.013	-0.025	-0.017	-0.021	-0.036	-0.044
	(0.106)	(0.106)	(0.108)	(0.106)	(0.106)	(0.106)	(0.107)	(0.107)
yrs_educ	-0.152**	-0.152**	-0.153**	-0.159**	-0.168**	-0.153**	-0.176***	-0.176***
	(0.066)	(0.066)	(0.066)	(0.067)	(0.066)	(0.066)	(0.066)	(0.067)
educsqr	0.007**	0.007**	0.007**	0.007**	0.008***	0.007**	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
hhsize	-0.009	-0.009	-0.010	-0.011	-0.011	-0.007	-0.008	-0.007
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
tenure	-0.004	-0.004	-0.004	-0.004	-0.003	-0.003	-0.004	-0.003

	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
firmsize1	0.382**	0.382*	0.391**	0.383**	0.397**	0.393**	0.371*	0.383**
	(0.193)	(0.196)	(0.194)	(0.194)	(0.193)	(0.194)	(0.194)	(0.194)
firmsize2	0.141	0.141	0.146	0.141	0.151*	0.148*	0.143	0.146
	(0.089)	(0.089)	(0.089)	(0.089)	(0.088)	(0.089)	(0.088)	(0.089)
firmsize3	0.167**	0.167**	0.166**	0.166**	0.172**	0.175**	0.182**	0.185**
	(0.075)	(0.075)	(0.075)	(0.075)	(0.074)	(0.075)	(0.075)	(0.075)
Openness		-0.001					0.334**	
		(0.049)					(0.147)	
Conscientious			-0.042				-0.570*	
			(0.070)				(0.321)	
Extraversion				-0.035			-1.532**	-0.187*
				(0.046)			(0.753)	(0.103)
Agreeableness					-0.080		1.376*	
					(0.049)		(0.751)	
Neuroticism						0.044	0.912**	0.141**
						(0.041)	(0.440)	(0.069)
cluster1								0.057
								(0.049)
R^2	0.160	0.160	0.162	0.163	0.173	0.166	0.202	0.183
Adj. R^2	0.110	0.105	0.107	0.108	0.118	0.111	0.130	0.120
Num. obs.	195	195	195	195	195	195	195	195
RMSE	0.449	0.450	0.450	0.450	0.447	0.449	0.444	0.447

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.13: Personality, shocks and involuntary mobility

Estimated Multinomial Logit Coefficients on Employee Mobility

	(a)			(b)			(c)		
	voluntary	**retrench**	**closed**	**voluntary**	**retrench**	**closed**	**voluntary**	**retrench**	**closed**
(Intercept)	4.799**	1.021	-4.575	5.162**	1.641	-3.785	5.186**	1.584	-3.749
	(2.062)	(2.263)	(3.596)	(2.130)	(2.307)	(3.704)	(2.146)	(2.344)	(3.716)
age	-0.189**	-0.090	0.036	-0.202**	-0.116	0.000	-0.202**	-0.116	-0.002
	(0.086)	(0.083)	(0.133)	(0.088)	(0.085)	(0.136)	(0.089)	(0.086)	(0.136)
agesqr/100	2.132**	1.284	-0.176	2.238**	1.617*	0.182	2.253**	1.606*	0.207
	(0.965)	(0.920)	(1.445)	(0.980)	(0.943)	(1.475)	(0.996)	(0.953)	(1.484)
male	0.413	-0.651*	-0.180	0.415	-0.785**	-0.194	0.416	-0.826**	-0.205
	(0.413)	(0.333)	(0.502)	(0.422)	(0.342)	(0.517)	(0.425)	(0.348)	(0.519)
married	-0.624	-0.826**	0.242	-0.701	-0.843**	0.122	-0.683	-0.809*	0.127
	(0.441)	(0.410)	(0.714)	(0.443)	(0.418)	(0.715)	(0.447)	(0.423)	(0.717)
yrs_educ	-0.556**	-0.124	0.106	-0.556**	-0.146	0.120	-0.561**	-0.144	0.124
	(0.227)	(0.299)	(0.456)	(0.229)	(0.303)	(0.467)	(0.228)	(0.305)	(0.467)
educsqr	0.027***	0.005	-0.006	0.027***	0.006	-0.008	0.027***	0.006	-0.008
	(0.010)	(0.013)	(0.020)	(0.010)	(0.013)	(0.021)	(0.010)	(0.013)	(0.021)
hhsize	0.053	0.130*	-0.055	0.052	0.139**	-0.053	0.053	0.148**	-0.051
	(0.075)	(0.069)	(0.100)	(0.076)	(0.070)	(0.103)	(0.076)	(0.071)	(0.103)
tenure	-0.034*	-0.028	-0.010	-0.033	-0.031*	-0.009	-0.034	-0.032*	-0.009
	(0.021)	(0.017)	(0.021)	(0.021)	(0.017)	(0.021)	(0.021)	(0.017)	(0.021)
shock	0.083	0.117	1.473***	0.151	0.163	1.587***	0.148	0.177	1.592***
	(0.313)	(0.292)	(0.424)	(0.321)	(0.299)	(0.434)	(0.324)	(0.302)	(0.436)
Extraversion				-0.482	0.508	-0.963	-2.203	9.340***	0.629
				(0.455)	(0.443)	(0.637)	(3.190)	(3.478)	(2.436)
Neuroticism				0.390	-0.508*	0.809**	1.409	-5.689***	-0.128
				(0.301)	(0.299)	(0.385)	(1.886)	(2.040)	(1.417)

cluster1				0.271	-0.006	0.582*			
				(0.211)	(0.178)	(0.306)			
Openness							0.510	-1.460**	0.266
							(0.629)	(0.692)	(0.599)
Conscientious							-0.464	3.483**	1.090
							(1.296)	(1.393)	(1.032)
Agreeableness							1.963	-8.749***	-1.157
							(3.213)	(3.365)	(2.381)
AIC	948.500	948.500	948.500	950.778	950.778	950.778	957.022	957.022	957.022
BIC	1077.024	1077.024	1077.024	1117.859	1117.859	1117.859	1149.808	1149.808	1149.808
Log Likelihood	-444.250	-444.250	-444.250	-436.389	-436.389	-436.389	-433.511	-433.511	-433.511
Deviance	888.500	888.500	888.500	872.778	872.778	872.778	867.022	867.022	867.022
Num. obs.	536	536	536	536	536	536	536	536	536

***p < 0.01, **p < 0.05, *p < 0.1

Table B.14: Personality, shocks and involuntary mobility

Estimated Multinomial Logit Coefficients on Employee Mobility

	(a)			(b)			(c)		
	voluntary	**retrench**	**closed**	**voluntary**	**retrench**	**closed**	**voluntary**	**retrench**	**closed**
(Intercept)	4.901**	1.026	-5.135	5.141**	1.562	-4.953	5.183**	1.495	-4.809
	(2.092)	(2.284)	(3.740)	(2.152)	(2.322)	(3.986)	(2.162)	(2.356)	(3.993)
age	-0.211**	-0.106	0.053	-0.220**	-0.130	0.030	-0.219**	-0.129	0.023
	(0.086)	(0.083)	(0.139)	(0.088)	(0.085)	(0.143)	(0.089)	(0.086)	(0.143)
agesqr/1000	2.326**	1.435	-0.246	2.400**	1.749*	-0.019	2.403**	1.732*	0.063
	(0.965)	(0.923)	(1.509)	(0.979)	(0.947)	(1.545)	(0.995)	(0.956)	(1.556)
male	0.377	-0.704**	-0.583	0.390	-0.828**	-0.626	0.395	-0.865**	-0.658
	(0.416)	(0.337)	(0.552)	(0.424)	(0.345)	(0.576)	(0.427)	(0.351)	(0.579)
married	-0.620	-0.842**	0.141	-0.707	-0.857**	0.193	-0.694	-0.820*	0.243
	(0.440)	(0.410)	(0.761)	(0.444)	(0.419)	(0.776)	(0.448)	(0.424)	(0.786)
yrs_educ	-0.569**	-0.098	0.241	-0.563**	-0.113	0.282	-0.573**	-0.115	0.288
	(0.236)	(0.304)	(0.484)	(0.238)	(0.308)	(0.512)	(0.235)	(0.309)	(0.514)
educsqr	0.028***	0.004	-0.011	0.027***	0.005	-0.014	0.027***	0.005	-0.014
	(0.010)	(0.013)	(0.021)	(0.010)	(0.013)	(0.022)	(0.010)	(0.013)	(0.022)
hhsize	0.057	0.135*	-0.067	0.057	0.145**	-0.067	0.056	0.153**	-0.068
	(0.076)	(0.070)	(0.102)	(0.077)	(0.071)	(0.106)	(0.076)	(0.072)	(0.107)
tenure	-0.033	-0.025	-0.007	-0.032	-0.028	-0.006	-0.033	-0.031*	-0.006
	(0.021)	(0.017)	(0.022)	(0.021)	(0.017)	(0.023)	(0.021)	(0.017)	(0.023)
shock	0.127	0.164	1.437***	0.192	0.201	1.523***	0.183	0.222	1.565***
	(0.316)	(0.296)	(0.447)	(0.323)	(0.301)	(0.458)	(0.325)	(0.305)	(0.466)
micro	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)		(0.000)	(0.000)		(0.000)			
small	0.966**	0.813**	0.463	0.957**	0.764*	0.475	0.946**	0.721*	0.448
	(0.439)	(0.397)	(0.426)	(0.441)	(0.398)	(0.442)	(0.443)	(0.400)	(0.444)
medium	0.657*	0.124	-9.288***	0.651*	0.106	-15.995***	0.647*	0.117	-15.260***
	(0.350)	(0.327)	(0.000)	(0.350)	(0.329)	(0.000)	(0.351)	(0.333)	(0.000)
Extraversion				-0.474	0.500	-0.985	-2.250	8.933**	-0.842
				(0.461)	(0.445)	(0.629)	(3.291)	(3.850)	(1.871)
Neuroticism				0.410	-0.489	0.867**	1.460	-5.431**	0.755
				(0.306)	(0.301)	(0.398)	(1.941)	(2.255)	(1.107)
cluster1				0.255	-0.010	0.532*			
				(0.214)	(0.179)	(0.300)			
Openness							0.491	-1.404*	0.625
							(0.647)	(0.748)	(0.546)
Conscientious							-0.494	3.327**	0.377
							(1.340)	(1.538)	(0.854)
Agreeableness							2.013	-8.348**	0.171
							(3.313)	(3.730)	(1.838)

AIC	915.786	915.786	915.786	918.644	918.644	918.644	925.162	925.162	925.162
BIC	1070.015	1070.015	1070.015	1111.430	1111.430	1111.430	1143.653	1143.653	1143.653
Log Likelihood	-421.893	-421.893	-421.893	-414.322	-414.322	-414.322	-411.581	-411.581	-411.581
Deviance	843.786	843.786	843.786	828.644	828.644	828.644	823.162	823.162	823.162
Num. obs.	536	536	536	536	536	536	536	536	536

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix C

Table C.1: Probit model on choice of Gamble

Probit model on risk choice: Dependent variable is gamble (1 = gamble)

Gamble (1 = yes)	**1**	**2**	**3**	**4**	**5**
Risk_Amount	0.006	0.042**	0.025***	0.025***	0.024***
	(0.069)	(0.021)	(0.009)	(0.009)	(0.009)
Risk_Amount^2	0.002				
	(0.007)				
age	-0.003**	-0.002	-0.001	-0.002	-0.003
	(0.001)	(0.001)	(0.007)	(0.007)	(0.007)
male		0.074	-0.025	-0.026	-0.028
		(0.096)	(0.032)	(0.033)	(0.033)
married		-0.068*	-0.056	-0.046	-0.046
		(0.038)	(0.040)	(0.040)	(0.040)
Risk Amount:male		-0.022			
		(0.023)			
agesqr			0.007	0.019	0.033
			(0.081)	(0.081)	(0.082)
yrs_educ			0.019***	0.016***	0.015**
			(0.006)	(0.006)	(0.006)
informal			-0.021	-0.030	
			(0.032)	(0.033)	
log_wage				0.011	0.012
				(0.018)	(0.018)
Informal employment					-0.060
					(0.038)
Self-employment					0.006
					(0.051)
Num. obs.	859	859	859	814	814
Log Likelihood	-358.073	-354.792	-348.158	-325.064	-324.461
Deviance	716.147	709.584	696.316	650.128	648.922
AIC	724.147	721.584	712.316	668.128	668.922
BIC	743.170	750.118	750.362	710.446	715.942

Table C.2: Risk Attitudes and Individual Specific Characteristics

Risk aversion	1	2	3	4	5	6
age	-0.002	-0.006	-0.004	-0.007	-0.007	-0.009
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
agesqr	0.014	0.055	0.047	0.085	0.086	0.111
	(0.068)	(0.076)	(0.075)	(0.075)	(0.075)	(0.076)
male	0.035	0.024	0.019	0.009	-0.001	-0.002
	(0.029)	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)
married		0.053	0.051	0.047	0.041	0.044
		(0.033)	(0.032)	(0.032)	(0.032)	(0.032)
yrs_educ		-0.003	0.002	0.000	0.002	0.002
		(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
informal			0.142***	0.149***	0.132***	0.145***
			(0.030)	(0.031)	(0.031)	(0.031)
Bulawayo				-0.087***		-0.065**
				(0.026)		(0.030)
Gweru				-0.024		-0.043
				(0.047)		(0.051)
Mutare				0.036		0.057
				(0.048)		(0.051)
Ndebele					-0.109***	-0.067*
					(0.033)	(0.038)
Karanga					-0.027	-0.036
					(0.031)	(0.033)
Manyika					0.007	0.028
					(0.029)	(0.031)
Foreigner					0.058	0.053
					(0.155)	(0.154)
R^2	0.005	0.014	0.066	0.095	0.096	0.112
Adj. R^2	-0.002	0.001	0.051	0.074	0.073	0.082
Num. obs.	398	398	398	398	398	398
RMSE	0.224	0.223	0.218	0.215	0.215	0.214

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table C.3: Fixed effects probit model on risk and job mobility

Left job	Estimate	Std.Err	t-value	p-value
age	-0.106	0.070	-1.511	0.132
agesqr	1.393	0.795	1.753	0.081 *
male	-0.537	0.276	-1.940	0.053 *
Married	-0.021	0.328	-0.065	0.948
Yrs_educ	-0.196	0.297	0.661	0.509
educsqr	0.009	0.012	-0.772	0.441
hhsize	0.023	0.053	0.431	0.666
tenure	-0.035	0.014	-2.514	0.013 **
Risk_Aver	-0.706	0.416	-1.695	0.091 *
shock	0.656	0.230	2.847	0.005 ***

Table C.4: Risk Preferences and Employee Mobility: Interactions

Left job (1=yes)	1	2	3	4	5	6	7
Risk_Ave	0.085	-0.203	-0.350	-0.162**	-0.211	-0.183**	-0.121
	(0.309)	(0.201)	(0.399)	(0.080)	(0.152)	(0.093)	(0.184)
age	-0.006	-0.005	-0.005	-0.005	-0.005	-0.006	-0.005
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)
agesqr	0.105	0.107	0.109	0.103	0.109	0.121	0.105
	(0.142)	(0.142)	(0.142)	(0.136)	(0.142)	(0.155)	(0.141)
male	-0.077	-0.077	-0.076	-0.074	-0.076	-0.098	-0.087
	(0.062)	(0.062)	(0.062)	(0.060)	(0.062)	(0.070)	(0.075)
married	0.008	0.016	0.008	0.007	0.008	0.019	0.008
	(0.062)	(0.071)	(0.062)	(0.060)	(0.062)	(0.067)	(0.061)
yrs_educ	-0.001	-0.001	0.003	-0.001	-0.001	0.001	-0.001
	(0.010)	(0.010)	(0.012)	(0.009)	(0.010)	(0.011)	(0.010)
hhsize	0.007	0.006	0.006	0.006	0.006	0.006	0.006
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
log_tenure	-0.054**	-0.054**	-0.054**	-0.053**	-0.054**	-0.061**	-0.054**
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.030)	(0.027)
informal	-0.146***	-0.144***	-0.143***	-0.175***	-0.141***	-0.100	-0.145***
	(0.036)	(0.037)	(0.037)	(0.037)	(0.040)	(0.071)	(0.037)
permanent	-0.033	-0.033	-0.034	-0.031	-0.022	-0.021	-0.034
	(0.052)	(0.052)	(0.052)	(0.050)	(0.061)	(0.057)	(0.053)
age:Risk_Ave	-0.001						
	(0.002)						
married:Risk_Ave		0.010					
		(0.049)					
yrs_educ:Risk_Ave			0.004				
			(0.008)				
informal:Risk_Ave				0.446			
				(0.483)			
permanent:Risk_Ave					0.014		
					(0.040)		
training						-0.111**	
						(0.048)	
Risk_Ave:training						0.053	
						(0.420)	
male:Risk_Ave							-0.012
							(0.046)
Num. obs.	308	308	308	308	308	284	308
Log Likelihood	-124.46	-124.79	-124.70	-124.34	-124.75	-121.71	-124.77
Deviance	248.926	249.588	249.405	248.688	249.499	243.421	249.559
AIC	272.926	273.588	273.405	272.688	273.499	269.421	273.559
BIC	317.687	318.349	318.167	317.450	318.261	316.858	318.320

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table C.5: Estimated Multinomial Logit Coefficients on Risk and Nature of Job Mobility.

	(1)			(2)			(3)		
Left job (1=stay)	voluntary	retrench	closed	voluntary	retrench	closed	voluntary	retrench	closed
Risk_Ave	-1.214	-0.385	-2.277*	-1.150	-0.001	-1.717*	0.107	0.388	-5.502
	(1.355)	(1.106)	(1.170)	(1.289)	(0.994)	(1.003)	(2.205)	(1.577)	(3.933)
age	-0.344	0.095	0.212	-0.250	-0.004	0.237	-0.333	0.094	0.206
	(0.252)	(0.160)	(0.289)	(0.218)	(0.141)	(0.215)	(0.249)	(0.160)	(0.282)
agesqr	4.689	-0.448	-1.467	3.243	0.501	-2.206	4.509	-0.437	-1.397
	(2.981)	(1.795)	(3.178)	(2.636)	(1.574)	(2.406)	(2.942)	(1.789)	(3.068)
male	-1.894**	-1.337**	0.263	-1.606**	-0.864	0.791	-1.747*	-1.253*	0.108
	(0.892)	(0.654)	(1.364)	(0.755)	(0.594)	(1.142)	(0.901)	(0.665)	(1.343)
married	-0.570	-0.167	0.797	-0.534	-0.016	0.505	-0.752	-0.279	1.050
	(1.126)	(0.866)	(1.626)	(1.006)	(0.828)	(1.083)	(1.161)	(0.880)	(1.660)
yrs_educ	3.362*	0.237	0.576	2.062	-0.007	-0.130	3.176	0.270	0.560
	(2.007)	(0.569)	(0.990)	(1.705)	(0.490)	(0.549)	(1.947)	(0.563)	(1.018)
educsqr	-0.126	-0.012	-0.025	-0.078	-0.001	0.006	-0.120	-0.013	-0.023
	(0.077)	(0.024)	(0.044)	(0.065)	(0.021)	(0.025)	(0.075)	(0.024)	(0.045)
hhsize	0.304*	0.042	-0.431	0.268*	0.092	-0.349*	0.287*	0.044	-0.485*
	(0.157)	(0.143)	(0.268)	(0.153)	(0.124)	(0.198)	(0.155)	(0.141)	(0.287)
tenure	-0.069	-0.097**	-0.054	-0.033	-0.046	0.004	-0.061	-0.094**	-0.056
	(0.055)	(0.040)	(0.043)	(0.050)	(0.029)	(0.033)	(0.056)	(0.041)	(0.042)
shock	1.243*	0.635	3.468***				0.749	0.362	4.739**
	(0.732)	(0.591)	(1.146)				(0.963)	(0.709)	(2.228)
informal				3.389**	-12.324***	-12.284***			
				(1.691)	(0.000)	(0.000)			
shock:Risk_Ave							-2.373	-1.659	3.188
							(2.940)	(2.271)	(4.116)
AIC	275.585	275.585	275.585	336.048	336.048	336.048	279.642	279.642	279.642
BIC	371.459	371.459	371.459	436.904	436.904	436.904	384.232	384.232	384.232
Log Likelihood	-104.792	-104.792	-104.792	-135.024	-135.024	-135.024	-103.821	-103.821	-103.821
Deviance	209.585	209.585	209.585	270.048	270.048	270.048	207.642	207.642	207.642
Num. obs.	135	135	135	157	157	157	135	135	135

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix D

Table D.1: Probit model marginal effects on time choice and individual characteristics

Wait	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Time_amount	0.157*	0.133	0.141	0.167*	0.177*	0.178*
	(0.094)	(0.097)	(0.094)	(0.098)	(0.099)	(0.099)
I(Time_amount^2)	-0.009	-0.009	-0.007	-0.009	-0.010	-0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
male		-0.197				
		(0.149)				
Time_amount:male		0.024				
		(0.036)				
yrs_educ			0.015*	0.022**	0.019**	0.018**
			(0.008)	(0.009)	(0.009)	(0.009)
age			0.001	0.011	-0.000	0.004
			(0.010)	(0.010)	(0.011)	(0.010)
agesqr			0.044	-0.050	0.057	0.007
			(0.114)	(0.119)	(0.124)	(0.121)
log_wage				-0.078***	-0.096***	-0.076**
				(0.026)	(0.027)	(0.031)
OCCinfor_emp					-0.302***	
					(0.068)	
OCCself_emp					-0.137*	
					(0.079)	
informal						0.101
						(0.300)
log_wage:informal						-0.060
						(0.060)
Num. obs.	797	797	797	746	746	746
Log Likelihood	-513.437	-510.744	-508.155	-467.969	-457.864	-458.755
Deviance	1026.875	1021.488	1016.311	935.939	915.727	917.509
AIC	1032.875	1031.488	1028.311	949.939	933.727	935.509
BIC	1046.918	1054.892	1056.396	982.242	975.260	977.042

***p < 0.01, **p < 0.05, *p < 0.1

Table D.2: Time Preferences and Individual Characteristics (Exponential)

Exponential	1	2	3	4	5	6
(Intercept)	0.135***	0.133***	0.136***	0.112***	0.107*	0.115*
	(0.019)	(0.019)	(0.038)	(0.039)	(0.063)	(0.063)
age	-0.001*	-0.001**	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.003)	(0.003)
male	-0.001	-0.001	-0.001	-0.004	0.001	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Ndebele	-0.038***					-0.028**
	(0.013)					(0.014)
Karanga	-0.000					-0.001
	(0.013)					(0.013)
Manyika	-0.006					-0.002
	(0.013)					(0.014)

Foreigner	-0.006					-0.007
	(0.075)					(0.076)
married		0.017	0.017	0.019	0.017	0.016
		(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Bulawayo		-0.023**	-0.024**	-0.025**	-0.024**	-0.014
		(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Gweru		-0.004	-0.005	0.000	0.000	0.001
		(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
Mutare		0.001	0.000	0.006	0.006	0.005
		(0.022)	(0.022)	(0.022)	(0.022)	(0.024)
yrs_educ			-0.000	0.000	0.000	0.000
			(0.002)	(0.002)	(0.002)	(0.002)
tenure			-0.000		-0.000	
			(0.001)		(0.001)	
informal				0.027**	0.053*	0.055*
				(0.013)	(0.031)	(0.031)
agesqr					-0.001	-0.001
					(0.032)	(0.033)
male:informal					-0.030	-0.035
					(0.034)	(0.034)
R^2	0.018	0.016	0.016	0.021	0.023	0.029
Adj. R^2	0.010	0.008	0.006	0.011	0.009	0.011
Num. obs.	780	781	781	781	781	780
RMSE	0.130	0.130	0.130	0.129	0.130	0.130

****p < 0.01, **p < 0.05, *p < 0.1*

Table D.3: Time Preferences and Individual Characteristics (Hyperbolic)

Hyperbolic	**1**	**2**	**3**	**4**	**5**	**6**
(Intercept)	0.358	0.466	0.526	0.941	1.133	1.237
	(0.450)	(0.442)	(0.868)	(0.906)	(1.455)	(1.466)
age	0.010	0.001	0.011	-0.003	-0.008	-0.016
	(0.010)	(0.010)	(0.014)	(0.011)	(0.066)	(0.066)
male	-0.158	-0.218	-0.202	-0.198	-0.197	-0.261
	(0.277)	(0.282)	(0.284)	(0.285)	(0.315)	(0.316)
Ndebele	-0.297					-0.122
	(0.297)					(0.329)
Karanga	0.226					0.386
	(0.292)					(0.311)
Manyika	-0.397					-0.289
	(0.300)					(0.314)
Foreigner	-0.524					-0.359
	(1.753)					(1.782)
married		0.422	0.423	0.399	0.441	0.424
		(0.302)	(0.302)	(0.303)	(0.331)	(0.334)
Bulawayo		-0.374	-0.405*	-0.372	-0.400	-0.282
		(0.239)	(0.242)	(0.242)	(0.243)	(0.269)
Gweru		-0.531	-0.570	-0.587	-0.638	-0.391
		(0.586)	(0.587)	(0.589)	(0.591)	(0.613)
Mutare		-0.523	-0.561	-0.584	-0.636	-0.853
		(0.514)	(0.515)	(0.518)	(0.520)	(0.551)
yrs_educ			-0.022	-0.022	-0.030	-0.025
			(0.051)	(0.051)	(0.052)	(0.052)

tenure			-0.020		-0.022	
			(0.015)		(0.015)	
informal				-0.276	-0.468	-0.417
				(0.297)	(0.721)	(0.723)
agesqr					0.197	0.179
					(0.753)	(0.759)
male:informal					0.160	0.106
					(0.783)	(0.788)
R^2	0.006	0.009	0.011	0.010	0.013	0.015
Adj. R^2	-0.001	0.001	0.001	-0.000	-0.001	-0.003
Num. obs.	783	784	784	784	784	783
RMSE	3.015	3.010	3.010	3.012	3.013	3.018

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table D.4: Probit model on outstanding salaries

	Basic model		Exponential Discounting			Hyperbolic Discounting		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expon			0.027	0.121	0.008			
			(0.191)	(0.197)	(0.219)			
Hyper						-0.007	-0.003	-0.004
						(0.008)	(0.008)	(0.009)
age	-0.010	-0.013		0.034*	0.029		0.034*	0.029
	(0.012)	(0.013)		(0.020)	(0.024)		(0.020)	(0.024)
agesqr	0.156	0.194		-0.307	-0.263		-0.310	-0.266
	(0.133)	(0.146)		(0.222)	(0.256)		(0.222)	(0.256)
male	0.049	0.032		-0.011	-0.041		-0.009	-0.043
	(0.049)	(0.053)		(0.076)	(0.083)		(0.076)	(0.083)
married	0.051	-0.005		0.017	-0.105		0.022	-0.103
	(0.057)	(0.064)		(0.087)	(0.106)		(0.087)	(0.106)
log_wage	-0.130***	-0.135***		-0.169***	-0.170***		-0.162***	-0.167***
	(0.032)	(0.035)		(0.047)	(0.052)		(0.047)	(0.052)
yrs_educ	0.061	0.073		0.003	0.004		0.004	0.005
	(0.047)	(0.049)		(0.013)	(0.060)		(0.013)	(0.060)
educsqr	-0.002	-0.002			0.000			0.000
	(0.002)	(0.002)			(0.003)			(0.003)
hhsize	0.003	0.004			0.016			0.017
	(0.009)	(0.010)			(0.017)			(0.017)
log_tenure	0.054**	0.064**			0.048			0.047
	(0.025)	(0.028)			(0.043)			(0.043)
Textiles, leather	-0.043	-0.084	-0.013	-0.075	-0.111	-0.009	-0.073	-0.115
	(0.062)	(0.067)	(0.089)	(0.091)	(0.102)	(0.089)	(0.090)	(0.101)
Wood products	-0.033	-0.055	0.059	0.028	0.031	0.052	0.017	0.026
	(0.068)	(0.074)	(0.099)	(0.102)	(0.115)	(0.098)	(0.101)	(0.115)
Chemicals	0.148**	0.137*	0.218**	0.228**	0.221*	0.217**	0.219**	0.219*
	(0.073)	(0.079)	(0.102)	(0.110)	(0.123)	(0.102)	(0.110)	(0.123)
Rubber, plastics	-0.012	-0.047	0.091	0.096	0.046	0.082	0.083	0.041
	(0.064)	(0.072)	(0.095)	(0.101)	(0.117)	(0.095)	(0.101)	(0.116)
Metals, machinery	0.135**	0.093	0.193**	0.175*	0.090	0.191**	0.171*	0.088
	(0.066)	(0.074)	(0.094)	(0.098)	(0.113)	(0.094)	(0.098)	(0.113)
Remittances	-0.057	-0.029	-0.056	-0.111	-0.075	-0.056	-0.109	-0.072
	(0.050)	(0.054)	(0.073)	(0.073)	(0.081)	(0.073)	(0.073)	(0.081)
Other jobs	-0.036	-0.038	-0.035	-0.018	-0.044	-0.036	-0.021	-0.043
	(0.039)	(0.042)	(0.056)	(0.059)	(0.062)	(0.056)	(0.059)	(0.062)

shock		0.164***			0.167***			0.169***
		(0.040)			(0.061)			(0.061)
small		0.149	0.045	-0.039	0.023	0.059	-0.029	0.025
		(0.152)	(0.133)	(0.143)	(0.244)	(0.133)	(0.144)	(0.244)
medium		0.100	-0.033	-0.126	-0.102	-0.032	-0.127	-0.102
		(0.144)	(0.121)	(0.135)	(0.231)	(0.121)	(0.135)	(0.231)
large		0.140	0.065	0.007	0.018	0.067	0.004	0.018
		(0.146)	(0.124)	(0.140)	(0.237)	(0.124)	(0.140)	(0.237)
Num. obs.	818	735	390	377	338	391	378	338
Log Likelihood	-523.753	-458.290	-255.651	-236.003	-205.610	-256.260	-237.242	-205.493
Deviance	1047.506	916.581	511.303	472.006	411.221	512.520	474.483	410.986
AIC	1081.506	958.581	535.303	508.006	455.221	536.520	510.483	454.986
BIC	1161.523	1055.178	582.897	578.786	539.328	584.145	581.311	539.093

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix E:

Table E.1: Descriptive statistics, disaggregated by sub-samples

	Time			Risk			Worker Sample			
Variable	**for**	**inform**	**p-value**	**formal**	**inform**	**p-value**	**formal**	**inform**	**p-value**	**Total**
Age	41.28	32.14	0.000	41.96	34.61	0.000	41.61	33.36	0.000	40.12
	(11.13)	(9.15)		(11.96)	(9.82)		(11.57)	(9.55)		(11.67)
Male	0.79	0.86	0.069	0.81	0.82	0.750	0.80	0.84	0.115	0.81
	(0.41)	(0.35)		(0.39)	(0.38)		(0.40)	(0.36)		(0.39)
Married	0.83	0.65	0.000	0.83	0.76	0.054	0.83	0.71	0.000	0.81
	(0.38)	(0.48)		(0.37)	(0.43)		(0.38)	(0.46)		(0.39)
Year education	11.45	11.18	0.109	11.46	11.01	0.007	11.46	11.09	0.002	11.39
	(2.38)	(1.79)		(2.43)	(1.70)		(2.40)	(1.74)		(2.30)
Household size	4.53	3.97	0.000	4.55	4.14	0.011	4.54	4.06	0.000	4.46
	(1.93)	(1.58)		(2.02)	(1.69)		(1.98)	(1.63)		(1.93)
Tenure	12.21	5.34	0.000	13.21	6.29	0.000	12.73	5.80	0.000	11.50
	(10.41)	(5.51)		(11.39)	(6.36)		(10.93)	(5.94)		(10.56)
Experience	5.44	3.97	0.002	5.64	4.76	0.105	5.53	4.36	0.001	5.33
	(6.99)	(4.40)		(7.37)	(5.47)		(7.18)	(4.96)		(6.87)
Monthly earning	392.77	297.36	0.058	364.90	283.70	0.046	378.09	290.50	0.006	346.76
	(460.26)	(548.55)		(284.48)	(458.63)		(378.47)	(504.56)		(269.91)
Total	**647**	**152**		**712**	**148**		**1362**	**300**		**1662**

Note: sample means and sd in parenthesis.

Table E.2: Multinomial logit average marginal effects on the probability of employment in a given occupational sector.

	(a)		(b)		(c)		(d)	
	informal	**self emp**	**informal**	**self emp**	**informal**	**self emp**	**informal**	**self emp**
Extraversion	-0.052***	-0.023	-0.105***	-0.112**	-0.027	-0.013	-0.032	-0.015
	(0.021)	(0.021)	(0.036)	(0.055)	(0.035)	(0.032)	(0.034)	(0.034
Neuroticism	0.036***	0.022*	0.030	0.078**	0.020	0.030	0.024**	0.032
	(0.014)	(0.013)	(0.029)	(0.035)	(0.022)	(0.021)	(0.022)	(0.021)
cluster1	0.028***	0.018**	0.038**	0.093***	0.026*	0.017	0.028*	0.017
	(0.010)	(0.010)	(0.017)	(0.033)	(0.015)	(0.014)	(0.015)	(0.015)
Risk Aversion			0.118**	0.347***				
			(0.080)	(0.107)				
Exponential					0.156**	0.019		
					(0.077)	(0.071)		
Hyperbolic							-0.002	-0.011
							(0.006)	(0.243)
age	-0.017***	0.019***	-0.009	0.017	-0.024***	0.017**	-0.024***	0.017
	(0.004)	(0.006)	(0.014)	(0.115)	(0.006)	(0.009)	(0.006)	(0.009)
agesqr	0.116**	-0.262***	-0.019	-0.216	0.195**	-0.257**	0.196**	-0.256**
	(0.569)	(0.075)	(0.139)	(0.142)	(0.081)	(0.116)	(0.080)	(0.116)
male	0.019	0.023	-0.000	-0.017	0.050*	0.023	-0.048	-0.022
	(0.018)	(0.018)	(0.037)	(0.037)	(0.029)	(0.028)	(0.029)	(0.027)
married	-0.007	0.005	-0.025	-0.016	-0.020	-0.004	-0.017	-0.002
	(0.017)	(0.213)	(0.039)	(0.047)	(0.026)	(0.030)	(0.026)	(0.030)
hhsize	-0.011***	0.002	-0.004	-0.001	-0.015**	0.008	-0.016*	0.008
	(0.004)	(0.004)	(0.007)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
yrs_educ	0.024	-0.013	0.028	0.016	0.028	-0.022	0.029	-0.021
	(0.022)	(0.016)	(0.044)	(0.062)	(0.036)	(0.021)	(0.036)	(0.021)
educsqr	-0.003**	0.000	-0.004	-0.004	-0.002	0.022	-0.002	0.001
	(0.001)	(0.001)	(0.007)	(0.008)	(0.001)	(0.020)	(0.001)	(0.001)
Ndebele	-0.011	-0.031*	-0.079*	-0.030	0.011	-0.025	-0.003	-0.028
	(0.018)	(0.017)	(0.039)	(0.045)	(0.028)	(0.027)	(0.027)	(0.027)
Karanga	0.007	-0.002	-0.059	0.046	0.040	-0.018	0.037	-0.019
	(0.019)	(0.019)	(0.038)	(0.044)	(0.027)	(0.026)	(0.027)	(0.026)
Manyika	-0.029*	-0.028*	-0.079**	-0.040	0.012	-0.037	0.006	-0.039
	(0.018)	(0.017)	(0.031)	(0.028)	(0.028)	(0.025)	(0.028)	(0.025)
Foreigner	0.057	-0.089***	-0.136***	-0.085***	0.341	-0.094***	0.334	-0.096***
	(0.126)	(0.011)	(0.022)	(0.019)	(0.230)	(0.017)	(0.230)	(0.016)
Num. obs.	1655	1655	396	396	776	776	779	779

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E.3: Mincer Earnings Equation: Personality traits, risk and time preferences

Log wage	1	2	3	4	5	6	7	8
Openness		0.080						
		(0.069)						
Conscientious		-0.020						
		(0.148)						
Extraversion		-0.216	-0.102**	-0.048	-0.074	-0.091	-0.108*	-0.079
		(0.365)	(0.049)	(0.076)	(0.080)	(0.081)	(0.056)	(0.049)
Agreeableness		0.141						
		(0.368)						
Neuroticism		0.130	0.066**	0.007	0.099*	0.109**	0.056	0.059*
		(0.215)	(0.033)	(0.055)	(0.052)	(0.052)	(0.038)	(0.033)
cluster1			0.046**	0.030	0.038	0.043	0.033	0.030
			(0.021)	(0.032)	(0.035)	(0.035)	(0.024)	(0.021)
Risk Aversion				0.140				
				(0.129)				
Hyperbolic					0.018**			
					(0.008)			
Exponential						0.302		
						(0.187)		
age	0.031***	0.030***	0.031***	0.011	0.050***	0.050***	0.030**	0.044***
	(0.010)	(0.010)	(0.010)	(0.018)	(0.016)	(0.017)	(0.012)	(0.010)
agesqr	-0.393***	-0.385***	-0.391***	-0.177	-0.609***	-0.606***	-0.377***	-0.526***
	(0.117)	(0.117)	(0.117)	(0.209)	(0.185)	(0.186)	(0.138)	(0.115)
male	0.227***	0.227***	0.229***	0.235***	0.284***	0.281***	0.212***	0.219***
	(0.044)	(0.044)	(0.044)	(0.077)	(0.070)	(0.070)	(0.052)	(0.045)
married	0.148***	0.149***	0.147***	0.117	0.087	0.089	0.152**	0.160***
	(0.050)	(0.050)	(0.050)	(0.084)	(0.077)	(0.078)	(0.060)	(0.050)
experience	0.016**	0.016**	0.015**	0.029**	0.008	0.008	0.015**	0.015**
	(0.007)	(0.007)	(0.007)	(0.012)	(0.011)	(0.011)	(0.008)	(0.007)
expersq	0.003	0.003	0.004	-0.052	0.037	0.035	0.008	0.009
	(0.022)	(0.022)	(0.022)	(0.036)	(0.037)	(0.037)	(0.024)	(0.022)
tenure	0.007**	0.007**	0.007**	0.013**	0.008*	0.008*	0.007**	0.008***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
yrs_educ	-0.074*	-0.080*	-0.080*	-0.064	-0.056	-0.053	-0.070	-0.087**
	(0.042)	(0.042)	(0.042)	(0.077)	(0.062)	(0.062)	(0.047)	(0.043)
educsqr	0.007***	0.007***	0.007***	0.007**	0.006**	0.006**	0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
training	0.178***	0.181***	0.181***	0.255***	0.139*	0.139*	0.140**	0.205***
	(0.051)	(0.052)	(0.052)	(0.086)	(0.080)	(0.081)	(0.060)	(0.052)
informal	-0.334***	-0.356***	-0.349***	-0.382***	-0.356***	-0.371***		
	(0.062)	(0.064)	(0.063)	(0.112)	(0.096)	(0.097)		
shock							-0.077*	
							(0.040)	
(Intercept)	4.568***	4.633***	4.620***	4.794***	4.098***	4.065***	4.589***	4.260***
	(0.312)	(0.315)	(0.314)	(0.550)	(0.472)	(0.476)	(0.363)	(0.310)
R^2	0.199	0.203	0.202	0.295	0.207	0.202	0.141	0.185
Adj. R^2	0.193	0.194	0.195	0.263	0.190	0.184	0.130	0.178
Num. obs.	1453	1453	1453	350	681	678	1106	1453

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table E.4: Employee Mobility: Personality Traits, Risk and Time Preferences

Left job	1	2	3	4	5	6	7	8	9	10
cluster1		0.033**		0.049**	0.063**		0.011	0.011		
		(0.016)		(0.024)	(0.031)		(0.019)	(0.019)		
Extraversion		-0.029	0.376	-0.099*	-0.136*	0.040	0.016	0.014	-0.007	0.042
		(0.037)	(0.286)	(0.056)	(0.071)	(0.579)	(0.045)	(0.045)	(0.442)	(0.439)
Neuroticism		0.032	-0.207	0.063	0.083	-0.033	0.012	0.012	0.032	0.002
		(0.025)	(0.167)	(0.040)	(0.052)	(0.339)	(0.029)	(0.029)	(0.260)	(0.259)
Openness			-0.025			0.089			0.036	0.022
			(0.055)			(0.112)			(0.084)	(0.083)
Conscientious			0.182			0.082			-0.003	0.021
			(0.116)			(0.241)			(0.176)	(0.175)
Agreeableness			-0.388			-0.158			0.035	-0.013
			(0.284)			(0.572)			(0.441)	(0.438)
Risk Aversion				-0.172**	-0.215**	-0.217**				
				(0.081)	(0.101)	(0.101)				
Exponential							-0.171*		-0.093	
							(0.096)		(0.127)	
Hyperbolic								-0.003		-0.016
								(0.005)		(0.025)
agesqr	0.194***	0.185**	0.189**	0.145	0.093	0.098	0.309***	0.309***	0.273**	0.255**
	(0.065)	(0.082)	(0.082)	(0.135)	(0.176)	(0.178)	(0.098)	(0.099)	(0.126)	(0.126)
Male	-0.014	-0.035	-0.038	-0.088	-0.134	-0.157*	0.015	0.017	0.022	0.023
	(0.027)	(0.034)	(0.035)	(0.063)	(0.085)	(0.090)	(0.036)	(0.036)	(0.045)	(0.045)
married	-0.049	-0.086*	-0.083*	-0.003	-0.012	0.011	-0.020	-0.024	-0.081	-0.081
	(0.035)	(0.046)	(0.046)	(0.062)	(0.080)	(0.077)	(0.045)	(0.046)	(0.069)	(0.068)
yrs_educ	-0.003	-0.005	-0.005	-0.006	-0.012	-0.013	-0.001	-0.002	-0.005	-0.005
	(0.005)	(0.006)	(0.006)	(0.010)	(0.012)	(0.012)	(0.007)	(0.007)	(0.008)	(0.008)
hhsize	0.003	0.005	0.005	0.005	0.003	0.002	-0.010	-0.010	-0.005	-0.006
	(0.005)	(0.006)	(0.006)	(0.010)	(0.012)	(0.012)	(0.008)	(0.008)	(0.010)	(0.010)
log_tenure	-0.043***	-0.071***	-0.071***	-0.057**	-0.135***	-0.145***	-0.059***	-0.057***	-0.064***	-0.063***
	(0.013)	(0.016)	(0.016)	(0.026)	(0.035)	(0.036)	(0.018)	(0.018)	(0.023)	(0.023)
informal	-0.145***			-0.144***			-0.155***	-0.159***		
	(0.017)			(0.033)			(0.021)	(0.021)		
shock		0.089***	0.090***		0.180***	0.181***			0.057	0.059
		(0.026)	(0.026)		(0.058)	(0.059)			(0.038)	(0.038)
Num. obs.	1251	901	901	308	228	228	591	593	413	414
Log Likelihood	-510.155	-377.97	-376.69	-122.78	-94.03	-92.832	-229.88	-233.85	-168.49	-170.54
Deviance	1020.311	755.953	753.388	245.579	188.077	185.663	459.768	467.704	336.983	341.080
AIC	1038.311	779.953	781.388	271.579	214.077	215.663	485.768	493.704	366.983	371.080
BIC	1084.496	837.595	848.637	320.070	258.658	267.103	542.732	550.711	427.335	431.468

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Note: dF/dx is for discrete change for the following variables- male, married, informal and shock. Standard errors are in parentheses. Cluster1 is a principal component of the three highly correlated personality trait variables (Openness, Conscientiousness and Agreeableness).